Lee, Boon Liat, Wilson, Clevo, Pasurka, Jr., Carl A., Fujii, Hidemichi, & Managi, Shunsuke
(2017)
Sources of airline productivity from carbon emissions: An analysis of operational performance under good and bad outputs.
Journal of Productivity Analysis, *47*(3), pp. 223-246.

Sources of airline productivity from carbon emissions: an analysis of operational performance under good and bad outputs*

B. L. Lee[a,**], C. Wilson[a], C. A. Pasurka, Jr.[b], H. Fujii[c] and S. Managi[d,a]

[a]*School of Economics and Finance, Queensland University of Technology, Brisbane, Queensland, Australia*

[b]*U.S. Environmental Protection Agency (1809T), Office of Policy, 1200 Pennsylvania Ave., N.W., Washington, D.C. 20460, USA*

[c]*Graduate School of Fisheries Science and Environmental Studies, Nagasaki University, Japan*

[d]*Urban Institute and Engineering, Kyushu University, Japan*

---

* Any errors, opinions, or conclusions are the authors' and should not be attributed to the U.S. Environmental Protection Agency. The authors would like to thank the two anonymous referees for providing useful comments and improving the paper.
** Corresponding author. Email: bl.lee@qut.edu.au.

Abstract

This study incorporates carbon dioxide emissions in productivity measurement in the airline industry and examines the determinants of productivity change. For this purpose a two-stage analysis under joint production of good and bad outputs is employed to compare the operational performance of airlines. In the first stage, productivity index are derived using the Luenberger productivity indicator. In the second stage, productivity change scores derived therefrom are regressed using the random-effects GLS to quantify determinants of productivity change. The paper finds low cost carriers and average number of hours flown per aircraft having a positive impact on productivity under joint production model while demand variable negatively impacts on productivity under market model.

Keywords
Productivity; Luenberger productivity indicator; pollution abatement; CO_2 emissions.

JEL classification
C43; D24; L93; Q50

1. Introduction

Since the 1990s, the airline industry has experienced unprecedented growth in competition largely from deregulation and entrants of low cost carriers (Assaf and Josiassen 2012). Low cost carriers (LCCs) once considered a nascent sector in the 1990s has now emerged as a major player in the airline industry contributing to one-third of output (Bhadra 2009).

To remain competitive in a deregulated market, airlines now compete aggressively via low fares, promotions, formation of global alliances and mergers while minimising costs. Consequently, competition has led to productivity gains through cost cutting measures especially for the LCCs which have succeeded in generating operating profits at low fares (Belobaba et al 2011). Competition, along with deregulation, has also led to state-owned European airlines either becoming fully or partially privatized leading to mergers such as Air France and KLM in 2004.

As a result of deregulation, rising competition, mergers and acquisitions, and entrants of LCCs into the airline industry, there is now a large extant literature on airline operational performance. Some notable studies include Good et al (1993), Banker and Johnston (1994), Distexhe and Perelman (1994), Good et al (1995), Gillen and Lall (1997), Tofallis (1997), Semenick and Sickles (1998), Coelli et al (1999), Adler and Golany (2001), Alam et al (2001), Sickles et al (2002), Scheraga (2004), Oum et al (2005), Greer (2006), Inglada et al (2006), Färe et al (2007), Barbot et al (2008), Greer (2008), Barros and Peypoch (2009), Bhadra (2009), Ouellette et al (2010), Assaf (2011), Belobaba et al (2011) and Assaf and Josiassen (2012). These studies assume a production approach in modelling airline operations, whereby aircraft flown over a distance transport passengers and freight.

From an input-output framework perspective, inputs such as labour, number of aircraft, and fuel burn are consumed to generate outputs such as revenue tonne kilometres, revenue passenger kilometres, and tonne kilometres performed. However, an aircraft burns fuel to transport passengers and freight, which inevitably generates carbon dioxide (CO_2). The theoretical input-output framework proposed by this study assumes that if aircraft are not flown, there are neither passenger kilometres nor CO_2 emissions, but if flown, the aircraft must burn fuel to carry passengers, thus generating both revenue passenger kilometres and CO_2. This framework thus suggests that the production of revenue passenger kilometres (a good output) produces a bad output (i.e., CO_2). The input-output framework employed in the above-mentioned studies considers only good outputs and does not incorporate bad outputs. As these studies focus on pre-2012 period and under an unregulated environment with no penalties for excessive CO_2 emissions, airlines have no incentive to reduce CO_2 emissions in a competitive market such as the airline industry. As such, the above studies assume that CO_2 emissions are freely disposable and excluded from the input-output framework.

So why should the current study include CO_2 emissions into the input-output framework and examine the determinants of the sources of efficiency change, technical change, and productivity change? This is because of global pressure for airline industries to incorporate CO_2 emissions in a managerial framework. Essentially, incorporating CO_2 emissions into the input-output framework would provide an alternative measure of airline operational performance as it considers how airlines allocate fixed resources to the production of more good outputs and less bad outputs. Initial work on this issue was undertaken by Lee et al (2015) using the Malmquist-Luenberger productivity index. They found that measures of productivity growth that ignore CO_2 emissions overstate the "true" productivity growth. The current paper makes further contributions (and improvements) to the issue of including CO_2 emissions into the input-output framework by carrying out a two-stage analysis to determine the sources of change in efficiency, technical change and productivity change.

As widely documented in airline annual reports for the past several years, airlines have been actively engaged in pollution abatement activities. In the Air Asia 2011 Annual Report, carbon emissions reduction were addressed through initiatives such as investment in fuel-efficient aircraft such as the Airbus A320 in 2004 and having monthly meetings to discuss ways and means to improve fuel efficiency by optimizing operating procedures (Air Asia 2011). In Emirates 2011 Annual Report, carbon emissions reduction was through the use of modern aircraft such as the Airbus A380, which is the Emirates flagship. In addition, Emirates also aimed at flying lighter by working together with manufacturers' airframe and propulsion engineers to reduce weight (Emirates 2011). The British Airways 2009-10 report states that carbon reduction is achieved by investing in new fuel-efficient aircraft such as the Boeing 777-300 ERs (British Airways 2011).

Reducing CO_2 emissions is also addressed through the adoption of sustainable alternative fuels. In February 2009, British Airways established a partnership with Solena to build Europe's first biomass to liquid plant to produce biofuel from 2014. In easyJet's 2011 Annual Report, the company acknowledges that choice of aircraft is beyond the company's control due to the highly regulated development of aircraft technology and that only fuel consumption is within their control. Hence, CO_2 emissions are reduced through their fuel efficiency programs such as changes to landing lights which reduces drag while in flight and relying on a single engine while taxiing aircraft before departure. In the Lufthansa 2011 Annual Report, its CO_2 reduction came in the form of using Quantum Lightweight Trolleys, a new line of thermal lightweight cabin service trolleys made from light composite materials thus reducing their weight, as well as greater seating capacity though modernizing the fleet. United Airlines 2009 Annual Report discusses plans to invest in 25 Boeing 787-8 Dreamliner aircraft and 25 Airbus A350 XWB aircrafts to replace the current fleet of international Boeing 747s and 767s with the goal of reducing its carbon emissions. The Singapore Airlines 2010-11 Annual Report shows that it implemented several initiatives to reduce carbon emissions. The initiatives include flight operations enhancements, engineering performance and maintenance improvements and weight saving measures to achieve optimum speeds for climb, cruise and descent of flights, and partnering with airport authorities to develop shorter and more direct flight routes.

From the above annual reports it can be seen that airlines are actively engaged in pollution abatement activities.[1] Airlines that engage in pollution abatement activities would, therefore, require re-allocation of existing resources, which is costly and more likely to reduce the production of good outputs given a fixed level of inputs. Hence, these airlines should be credited for reducing CO_2 emissions at the expense of reducing good outputs. Incorporating CO_2 emissions into the input-output

[1] The above selection is only a modest list solely to limit the number of pages of this article for brevity purpose.

framework would, therefore, provide a more accurate depiction of the production technology of airline operations. To incorporate CO_2 emissions into our input-output framework with a focus on productivity, we employ the directional distance function applying the Luenberger Productivity Indicator (LPI) as it is able to credit airlines for simultaneously reducing bad outputs and increasing good outputs.[2] Luenberger-type productivity is considered to be a more general measure than the widely used Malmquist-type Index (Chambers et al., 1998). Malmquist-Luenberger sometimes include large and rather unrealistic changes related to the low number of observations constituting the frontier on a year by year basis. However, the Luenberger indicator is approximately the log of the Malmquist index (see, Boussemart et al 2003) and is thus always substantially smaller, thereby mitigating the extreme results alluded to above.

Annual reports of airlines also suggest that pollution abatement activities vary across airlines ranging from adoption of new aircraft to improvements in operations and management largely driven by airline strategies, budget and objectives. Assuming that all airlines adopt pollution abatement activities, the rate at which these activities are adopted and how effective these activities are implemented will vary across airlines affecting productivity growth.

The importance of incorporating CO_2 as a bad output into our input-output framework thus raises three noteworthy questions: "Are there variations in productivity estimates between the case of accounting for bad output CO_2 and case of ignoring for it?" "Are LCCs or mainstream airlines more productive?" "What are the sources of changes in airline efficiency?" These questions form the objectives of our article.

The article is divided into five sections. Following the introduction, Section 2 describes the productivity model employed. Section 3 contains a description of the data and the input-output framework. The results are discussed in Section 4 and Section 5 provides some conclusions and suggestions for further research.

[2] The term 'productivity' used in this article does not refer to total-factor productivity but simply a general term. TFP is not referred to in this article because the Malmquist index of Caves, Christensen and Diewert (1982) and other derivatives (e.g. Luenberger) are not TFP indices as argued in O'Donnell (2010, 2012) and Peyrache (2014).

2. Empirical model: Luenberger Productivity Indicator

To measure productivity growth of airlines, the current study employs the LPI developed by Chambers and Pope (1996). We use a nonparametric linear programming model to operationalize the directional output distance function[3]. This can represent the production technology and allow for the inclusion of bad outputs without requiring information on shadow prices. It does not require the functional form relating inputs to outputs to be specified or to set weights for the various factors and credits producers for the simultaneous reduction of bad outputs and increase in good outputs. Notwithstanding, it is worth mentioning that the LPI can also be measured based on a parametric stochastic frontier approach which has been employed in Färe et al (2005) and Koutsomanoli-Filippaki et al (2009).

The directional output distance function with respect to two time-periods is defined as:

$$\vec{D}_0(x, y, b{:}\, g) = \sup[\beta(y, b) + \beta g \in P(x)] \tag{1}$$

where $\vec{D}_0(x, y, b{:}\, g)$ shows the technical inefficiency of airline, "g" is the direction vector in which outputs are scaled. In this paper, g = (y, -b), the production of good outputs, y (i.e., revenue tonne kilometres) is increased, while bad output -b (i.e., CO_2) is decreased. Furthermore, β is the maximum feasible expansion of desirable outputs and contraction of the bad outputs when the expansion and contraction are identical proportions for a given level of inputs. Since the theoretical framework behind the LPI is lengthy and for the sake of brevity, we direct readers to the following studies which include Chambers and Pope (1996), Chambers et al (1998), Färe et al (2001), Chambers (2002), Fujii et al (2010), and Fujii et al (2011).

The directional distance function expressed in (1) measures observations at time t based on the technology at time t+1. Hence the LPI between period t and t+1 is:

[3] A complete list of the axioms imposed on the technologies specified in this paper is found in Färe et al (2007).

$$LPI_t^{t+1} = \frac{1}{2}\left\{\begin{array}{c}\left(\vec{D}_0^{t+1}\left(x^t, y^t, b^t; y^t, -b^t\right) - \vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right) \\ + \left(\vec{D}_0^{t}\left(x^t, y^t, b^t; y^t, -b^t\right) - \vec{D}_0^{t}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right)\end{array}\right\} \qquad (2)$$

The LPI can be decomposed into efficiency change (EFFCH) and technical change (TECHCH). These are written as follows:

$$\mathrm{EFFCH}_t^{t+1} = \vec{D}_0^{t}\left(x^t, y^t, b^t; y^t, -b^t\right) - \vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right) \qquad (3)$$

$$TECHCH_t^{t+1} = \frac{1}{2}\left\{\begin{array}{c}\left(\vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right) - \vec{D}_0^{t}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right) \\ + \left(\vec{D}_0^{t+1}\left(x^t, y^t, b^t; y^t, -b^t\right) - \vec{D}_0^{t}\left(x^t, y^t, b^t; y^t, -b^t\right)\right)\end{array}\right\} \qquad (4)$$

The LPI indicates productivity improvement if values are greater than zero and deterioration in productivity if the values are less than zero.

Equation (3) measures the change in output efficiency between two periods. If $EFFCH_t^{t+1}$ exceeds zero, it indicates that an airline is closer to the frontier in period t + 1 than it was in period t. If the value is less than zero, then the airline is "falling behind" the frontier. Equation (4) measures technical change which illustrates shifts in the production possibilities frontier. If this shift is in the direction of more good outputs with fewer bad outputs, then the value of $TECHCH_t^{t+1}$ exceeds zero. If the value is less than zero, then technical regression has occurred.

In order to calculate the LPI and its decompositions, four distance functions which are specified as linear programming (LP) problems must be solved. Let us assume that if at a given time t=1,….T, there are k=1,…K airlines of inputs and outputs, the model can be expressed as:

$$P(x) = \{(y, b) \colon \textstyle\sum_{k=1}^{K} z_k\, y_{km}^t \geq y_m^t\ , m = 1, \ldots M. \qquad (5a)$$

$$\textstyle\sum_{k=1}^{K} z_k\, b_{kj}^t = b_j^t, j = 1, \ldots J. \qquad (5b)$$

$$\sum_{k=1}^{K} z_k \, x_{kn}^{t} \leq x_n^{t} \,, n = 1, \dots N. \tag{5c}$$

$$z_k \geq 0, \text{k} = 1, \dots \text{K}.\} \tag{5d}$$

which exhibits constant returns to scale so that:

$$P(\lambda x)=\lambda P(x), \lambda>0 \tag{6}$$

and strong disposability of inputs:

$$x' \geq x \Rightarrow P(x') \supseteq P(x) \tag{7}$$

The inequalities for inputs and good outputs in (5a) reflect the assumption that they are freely disposable. The bad outputs are assumed to be costly to dispose of and, therefore, are modelled as equalities. The non-negativity constraints on the intensity variables, z_k, allow the model to exhibit constant returns to scale.[4]

The treatment of bad outputs under the weak disposability assumption has been criticised because the manner in which it has been specified violates the first law of thermodynamics (Coelli et al., 2007 and Hoang and Coelli, 2011). The law states that pollution abatement does not eliminate the undesirable by-product of good output production but instead transforms the by-product from - for example - one medium (air) to another medium (land). Recently, concerns have been expressed about the theoretical and empirical implications of the failure of existing joint production models, which use weak disposability of outputs to model pollution abatement, to account for these material balance conditions. Dakpo et al. (2016) provide a survey of the extant literature on this topic.

The directional output distance functions for the LPI can be calculated as solutions to the four LP problems which are $\vec{D}_0^{t}\left(x^{t,k'}, y^{t,k'}, b^{t,k'}; y^{t,k'}, -b^{t,k'}\right)$, $\vec{D}_0^{t+1}\left(x^{t,k'}, y^{t,k'}, b^{t,k'}; y^{t,k'}, -b^{t,k'}\right)$,

[4] The rationale for constant returns to scale is that it is consistent with the vast majority of airline literature such as White (1979), Cornwell et al (1990), Good et al (1995) and Sickles et al (2002). As empirically demonstrated in Caves et al (1984) that U.S. large and small carriers could compete with one another over extended periods of time, an observation that is consistent with constant returns to scale.

$\vec{D}_0^{t+1}\left(x^{t+1,k\prime}, y^{t+1,k\prime}, b^{t+1,k\prime}; y^{t+1,k\prime}, -b^{t+1,k\prime}\right)$, and $\vec{D}_0^{t+1}\left(x^{t+1,k\prime}, y^{t+1,k\prime}, b^{t+1,k\prime}; y^{t+1,k\prime}, -b^{t+1,k\prime}\right)$.

These solutions are shown as follows:

$$\vec{D}_0^{t}\left(x^{t,k'}, y^{t,k'}, b^{t,k'}; y^{t,k'}, -b^{t,k'}\right) = \max\beta \tag{8a}$$

$$s.t. \sum_{k=1}^{K} z_k\, y_{km}^{t} \geq (1+\beta) y_{k\prime m}^{t} \text{ }, m = 1, \ldots M. \tag{8b}$$

$$\sum_{k=1}^{K} z_k\, b_{kj}^{t} = (1-\beta) b_{k\prime j}^{t} \text{ }, j = 1, \ldots J. \tag{8c}$$

$$\sum_{k=1}^{K} z_k\, x_{kn}^{t} \leq x_{k\prime n}^{t} \; n = 1, \ldots N. \tag{8d}$$

$$z_k \geq 0 \text{ }, k = 1, \ldots K. \tag{8e}$$

$$\vec{D}_0^{t+1}\left(x^{t,k'}, y^{t,k'}, b^{t,k'}; y^{t,k'}, -b^{t,k'}\right) = \max\beta \tag{9a}$$

$$s.t. \sum_{k=1}^{K} z_k\, y_{km}^{t+1} \geq (1+\beta) y_{k\prime m}^{t} \text{ }, m = 1, \ldots M. \tag{9b}$$

$$\sum_{k=1}^{K} z_k\, b_{kj}^{t+1} = (1-\beta) b_{k\prime j}^{t} \text{ }, j = 1, \ldots J. \tag{9c}$$

$$\sum_{k=1}^{K} z_k\, x_{kn}^{t+1} \leq x_{k\prime n}^{t} \; n = 1, \ldots N. \tag{9d}$$

$$z_k \geq 0 \text{ }, k = 1, \ldots K. \tag{9e}$$

$$\vec{D}_0^{t}\left(x^{t+1,k'}, y^{t+1,k'}, b^{t+1,k'}; y^{t+1,k'}, -b^{t+1,k'}\right) = \max\beta \tag{10a}$$

$$s.t. \sum_{k=1}^{K} z_k\, y_{km}^{t} \geq (1+\beta) y_{k\prime m}^{t+1} \text{ }, m = 1, \ldots M. \tag{10b}$$

$$\sum_{k=1}^{K} z_k\, b_{kj}^{t} = (1-\beta) b_{k\prime j}^{t+1} \text{ }, j = 1, \ldots J. \tag{10c}$$

$$\sum_{k=1}^{K} z_k\, x_{kn}^{t} \leq x_{k\prime n}^{t+1} \; n = 1, \ldots N. \tag{10d}$$

$$z_k \geq 0 \text{ }, k = 1, \ldots K. \tag{10e}$$

$$\vec{D}_0^{t+1}\left(x^{t+1,k'}, y^{t+1,k'}, b^{t+1,k'}; y^{t+1,k'}, -b^{t+1,k'}\right) = \max\beta \quad (11a)$$

$$s.t. \sum_{k=1}^{K} z_k\, y_{km}^{t+1} \geq (1+\beta) y_{k'm}^{t+1}, m = 1, \ldots M. \quad (11b)$$

$$\sum_{k=1}^{K} z_k\, b_{kj}^{t+1} = (1-\beta) b_{k'j}^{t+1}, j = 1, \ldots J. \quad (11c)$$

$$\sum_{k=1}^{K} z_k\, x_{kn}^{t+1} \leq x_{k'n}^{t+1}\ n = 1, \ldots N. \quad (11d)$$

$$z_k \geq 0, k = 1, \ldots K. \quad (11e)$$

A one-year window reference technology is employed in the study. This resembles Equation (9a) except that the time superscripts on the right-hand side of the constraints differ from the time superscripts on the left-hand side of the constraints. Under equation (9), the frontier line evaluating productive inefficiency in year t would be constructed using year t+1 data.

This study applies the directional output distance functions to two models; namely, the Market output based model and the Joint output based model. The Market model has combinations of input and output variables. In the Market model, LPI is estimated by the desirable outputs and inputs and bad output is ignored. Thus, LPI estimated by market model represent market competitiveness without considering bad output emissions. In the joint model, LPI is estimated by considering both good and bad output (i.e., CO_2 emissions) explicitly.

3. Data

Our primary source of data was purchased from RDC Aviation (http://www.rdcaviation.com/). The data is based on the International Air Transport Association (IATA) Scheduled Reference Service (SRS) database which contains over ninety-nine percent of all flight schedules worldwide thus ensuring that the data reflects those filed by the airlines themselves.

RDC Aviation provides time-series data on inputs and outputs that reflect airline operations and since they are drawn from a single source, the data are comparable. Secondary sources, such as Annual Reports, were used to fill data gaps after rigorous verification.

Our sample of thirty-four airlines comprise of twenty-one mainstream airlines and thirteen LCCs from 2004 to 2011. The airlines in our sample are based in six continents, with most from Asia, Europe and North America. While data on additional airlines are available from RDC Aviation, our sample is limited to thirty-four airlines due to funding constraints. Nonetheless, our sample size of mainstream airlines and LCCs over an eight-year period provides us with robust results.

Data specification of inputs and outputs follow a production approach to modelling airline operations, that is, aircraft flown over a distance consumes fuel which transports passengers and freight. Identifying inputs and outputs to satisfy the framework of airline production is a crucial part of the study and is heavily dependent on availability of reliable data. For a review of a list of inputs and outputs, we refer readers to Oum and Yu (1998); and Assaf and Josiassen (2012).

The production of good outputs inevitably generates CO_2 which is incorporated in our production framework of airline operations. The CO_2 emissions data are not values reported by the airlines but are estimates compiled by RDC Aviation. RDC Aviation has been compiling aviation CO_2 emissions data for over 10 years using its government-accredited emissions calculation engine which calculates fuel burn and conversion factors as directed by the Intergovernmental Panel for Climate Change and ratified using RDC proprietary systems. The methodology used in estimating CO_2 emissions are detailed in RDC Aviation 2011, *RDC Emissions Calculator: Methodology Document* (v.1.4). This document is available upon request from RDC Aviation. From the above discussion, we, therefore, identify two outputs: revenue tonne kilometres and CO_2.[5] As defined by International Civil Aviation Organization (ICAO), revenue tonne kilometres is the sum of the product obtained by multiplying the number of total tonnes of revenue load (passengers, freight and mail) carried on each flight stage by the stage distance which is the distance the aircraft has flown. Alternative output

[5] According to the U.S. Department of Transportation, Center for Climate Change and Environmental Forecasting, CO_2 constitutes roughly 70 percent of aircraft engine emissions. Although other pollutants such as NO_x are produced, we only consider CO_2 as this is the main pollutant emitted by airlines (Mendes and Santos 2008).

indicators such as revenue passenger kilometres (RPK) were not considered as RTK already includes all passengers, freight and mail. Hence, including RPK would result in double-counting.

With regard to inputs, past studies have used physical inputs such as number of employees, materials, aircraft capacity, fuel burned and number of aircraft. Some studies[6] have also considered financial indicators in both outputs and inputs. These financial outputs are measured in terms of earnings before interest and taxes (EBIT) or revenues, whereas financial inputs were measured in terms of operation costs. These studies have their merits when measuring performance in terms of cost efficiency analysis or financial performance comparisons.

From the literature and framework of our study, we identify four inputs: (i) fuel burned (ii) hours flown (iii) number of employees and (iv) average aircraft capacity. Fuel burned is the total amount of fuel consumed for all flights. Hours flown is the total number of hours of flight time. Number of employees consists of pilots, co-pilots and other cockpit personnel, cabin crew, maintenance and overhaul, and airport handling personnel. Average aircraft capacity is the number of seats per aircraft measured by taking the ratio of capacity (i.e. number of scheduled available seats) to number of aircraft. This input is a proxy for the average size of aircraft used in each airline and represents capital in our dataset. Ideally, total assets would be used but as this variable was not available for a number of airlines in RDC Aviation, we therefore rely on average aircraft capacity. Some studies use number of aircraft to represent capital, but because aircraft sizes vary across airlines we concluded this variable constitutes an inaccurate proxy for capital. Of the inputs, the number of employees required some adjustments for the following airlines: JAL, Air France, KLM, SAS, Philippine Airlines, easyJet, Virgin Australia, Transavia.com, AirTran Airways, Frontier Airlines and Southwest Airlines. For most, missing data were supplemented using annual reports. When these were not available or reported in annual reports, we estimated the number of employees based either on averages or extrapolations which follow similar growth patterns to other variables to justify our estimates.

[6] These include Barros and Peypoch (2009) and Assaf and Josiassen (2011).

The data used in the second stage regression analysis comprise of five variables which are both discretionary and non-discretionary in nature. *Membership* with some global airline alliance is a dummy variable. Thus *Member* = 1 represents a firm that belongs to some global airline alliance. As argued in Bissessur and Alamdari (1998), the authors demonstrated that under appropriate conditions, alliances increases the probability of success in terms of competitive position and cost reduction. It is noted that being a member does not mean that all global airlines alliances have the same effect as this is a weak assumption. While such specific data would provide invaluable insights on individual airline performance, the objective of this dummy variable is simply to determine whether there is a positive effect in being a member or not. Hence we consider airlines with some alliance having an advantage over non-alliance airlines. *LCC* (i.e., LCC versus mainstream airline) is a dummy variable to determine which airline type contributes positively to efficiency. *Ownership* (i.e. state-owned=0 versus privately-owned=1) is a dummy variable whereby state-ownership greater than 50 percent is considered state-owned and vice-versa. This variable will determine if privately owned airlines are more efficient than state-owned. *Demand,* measured by weight load factor (WLF), is an external factor and indicator of the ability of firms to behave efficiently in light of external market pressure (Bhadra 2009)[7]. It measures the tonne-kilometres performed expressed as a percentage of tonne-kilometres available. Because LCC offer low fares, we expect this factor to stimulate additional demand in air traffic and thus make LCC airlines more efficient than mainstream airlines. *Age* is an indicator for average fleet age. It is hypothesized that a younger, more modern fleet will have a positive impact on fuel efficiency and productivity.

Data for the second stage analysis are drawn from various sources. Information on whether an airline is a LCC or mainstream, whether a member of some global airline alliance, and whether state-owned or privately-owned are drawn from airline annual reports. WLF and number of flights are purchased from RDC Aviation. Average fleet age is drawn from http://www.airfleets.net/home/ (accessed on 2 October 2014).

[7] WLF includes tonnage of passengers, freight and mail. Hence, we do not consider passenger load factor since this is already included in WLF.

4. Results

4-1. Productivity change comparison: Market model vs Joint model

Summary statistics of inputs and outputs used in the first stage analysis are presented in Table 1. The data shows mean outputs and inputs in general increasing between 2004 and 2010 with the exception of 2009 which showed decline in all variables largely attributed to the global financial crisis. It is also observed that the maximum values for CO_2 show a reduction from 2006 to 2009. This suggests that reductions in CO_2 levels may be due to airlines adopting abatement activities in reducing CO_2 emissions.

Table 2 presents summary statistics of sources of productivity change that we use in the second stage regression analysis. From Table 2, 47 percent of sample firms belong to global airline alliances in 2010, 38 percent is LCC, and state-ownership firms represent 82 percent of sample in 2010.

[INSERT TABLE 1]

[INSERT TABLE 2]

Tables 3 and 4 present the LPI productivity change and their decompositions into efficiency change and technical change, respectively.[8] Table 3 shows the LPI productivity based on the market model ($\text{Productivity}_{\text{market}}$), which considers only the good output, in order to compare the results with the LPI productivity based on the joint model ($\text{Productivity}_{\text{joint}}$) shown in Table 4, which includes good and bad outputs, to identify variations in the results between the two methods.

[8] We also estimate each indicator applying 1,000 times bootstrap approach. Bootstrap approach in nonparametric frontier analysis allows us to calculate confidence intervals and statistical significance level (Simar and Wilson, 2000; Jeon and Sickles, 2004). The bootstrap estimation is widely applied in nonparametric frontier analysis with undesirable output (Yagi et al, 2015). We described the results of bootstrap estimation in Appendix 1-6. From the bootstrap estimation results, we confirm the consistent trend between the results in Tables 3 and 4, and confidence intervals in Appendix 1-6.

Table 3 shows eight LCCs are among the ten airlines with the highest $\text{Productivity}_{\text{market}}$ growth. Germanwings and Transavia.com were the LCC that exhibited negative productivity growth. From Table 4, six LCCs are among the ten airlines with the highest productivity growth rates. These six airlines – Skymark Airlines, Ryanair, WestJet, Norwegian, Southwest Airlines, and GOL – are in the top ten for both indices. Nine LCCs showed positive $\text{Productivity}_{\text{joint}}$ growth, while four LCCs - Germanwings, Virgin Australia, Transavia.com, and easyJet - posted negative $\text{Productivity}_{\text{joint}}$ growth. In terms of mainstream airlines in Table 4, only American Airline, Singapore Airline, Emirates and TAM made the top ten.

[INSERT TABLE 3]

[INSERT TABLE 4]

So what do these results suggest? With regard to our first objective "Are there variations in productivity estimates between the $\text{Productivity}_{\text{market}}$ and the $\text{Productivity}_{\text{joint}}$?", average annual productivity growth rates for $\text{Productivity}_{\text{market}}$ and $\text{Productivity}_{\text{joint}}$ were 4.27 and 1.77 percent, respectively. We observe that results from $\text{Productivity}_{\text{market}}$ show a wider gap between the highest and lowest productivity growth rates. Under $\text{Productivity}_{\text{market}}$, the highest productivity growth rate was 17.81 percent and the lowest was -2.99 percent, whereas under $\text{Productivity}_{\text{joint}}$, these were 10.52 and -2.95 percent, respectively. Standard deviation of TFP growth rates was 0.0522 and 0.0286 for $\text{Productivity}_{\text{market}}$ and $\text{Productivity}_{\text{joint}}$, respectively illustrating that the $\text{Productivity}_{\text{market}}$ show greater variation than the $\text{Productivity}_{\text{joint}}$. The above results also suggest that almost all airlines which embarked on pollution abatement activities had lower productivity growth rates. As noted by Färe et al (2007), the difference in productivity growth rates represent the effects associated with pollution abatement activities. This suggests that productivity growth which ignores CO_2 emissions does not accurately portray the production technology of airlines. By incorporating CO_2 emissions into the input-output framework, we provide a more accurate measure of airline performance.

4-2. Productivity change comparison: LCC vs mainstream airline

Table 3 and Table 4 shows the result of productivity estimation under Market model and Joint model. The bottom of the table, we describe the result of Mann–Whitney U test to check the statistical differences of productivity growth between mainstream firms and LCC firms.

For our second objective “Are LCCs or mainstream airlines more productive?”, we observe that most LCCs are ranked in the top ten and posted positive productivity growth rates under both indices. From Tables 3 and 4, higher productivity by LCCs is largely from efficiency change suggesting improvements in operations such as adoption of ‘best-practice’ management through improved resource allocation and/or reduction in organizational slack. In essence, LCC operations tend to be leaner than mainstream airlines as they have lower overheads and focus mainly on essential functions while cutting back on non-essentials. Furthermore, LCCs tend to have the usual practices of having standardized fleet, which suggests that employees operating under such conditions are more familiar with their tasks and hence more efficient than their counterparts in mainstream airlines which operate more heterogeneous fleets.

In Tables 3 and 4, productivity growth for mainstream airlines was attributed to improvements in efficiency change and to a lesser extent technical change. Further clarity on airline performance is obtained when we examine the technical inefficiency scores for each airline annually from 2004 to 2010 which highlights the improvements in efficiency.

Tables 5 and 6 present the results of technical inefficiency (TI) derived from the models market model and joint model, respectively. The bottom of the table, we show the result of Mann–Whitney U test to check the statistical differences of TI between mainstream firms and LCC firms.

Airlines with TI equaling zero are efficient whereas airlines having TI values greater than zero are inefficient. We observe that under both models, only Singapore Airlines, United Airlines, and Aer Lingus exhibit efficiency for the entire period which explains the technical inefficiency score equal zero for these airlines. With regards to the LCCs, we note that while they are relatively inefficient, it is observed that the majority of the LCCs decreased their inefficiency scores over time confirming that their productivity growth is largely due to improvements in technical efficiency

(EFFCH) as shown in Tables 3 and 4. It is also observed that the TI results between the two models show the market model exhibiting better airline performance especially for the LCCs suggesting that airlines are credited for the simultaneous reduction of bad outputs and increasing good outputs given fixed inputs.

[INSERT TABLE 5]

[INSERT TABLE 6]

4-3. Determinants of productivity change

For our third objective, "What are the sources of airline productivity?", we quantify the sources by regressing $\text{Productivity}_{\text{market}}$ and $\text{Productivity}_{\text{joint}}$ on several explanatory variables. We apply random-effects GLS regression to clarify the determinants of productivity change[9].

[TABLE 7 HERE]

[TABLE 8 HERE]

Table 7 and Table 8 provide the estimated coefficients and p-value for the second-stage estimation based on the random-effects GLS regression. Table 7 shows that LCC dummy variable is significantly positive for $\text{Productivity}_{\text{market}}$ and $\text{EFFCH}_{\text{market}}$. This result means $\text{Productivity}_{\text{market}}$ increased rapidly for LCCs comparing with mainstream airlines. Meanwhile, demand variable negatively affects $\text{Productivity}_{\text{market}}$ and $\text{EFFCH}_{\text{market}}$, which widens the productivity gap between inefficient and efficient airlines (airlines on the frontier line). Our finding on demand variable is consistent with the comment made in Coelli et al (1999, p.263) that "airlines operating with high load factor coefficient would expect an additional need in labour, essentially in cabin crew. Hence such a characteristic would be expected to be positively related to inefficiency".

[9] As alternative specifications, we run a generalized method of moments (GMM) (see Managi and Jena 2008). The results do not pass a Sargan test. In general, the estimated results are similar but less significant. This reflects smaller sample because we apply two year lag as instruments. These results are presented in Appendix 7 and 8.

Table 8 shows the determinants of $\text{Productivity}_{\text{joint}}$. From Table 8, the LCC dummy is no longer statistically significant illustrating that results based solely on good outputs can be misleading. When bad outputs are considered in the production model, the statistical insignificance suggests the presence of airlines adopting varying degrees of pollution abatement activities. The implication is that mainstream airlines emit more CO_2 than LCCs and are thus seen as leaders with a social responsibility which compels them to adopt strategies to reduce carbon emissions. As for LCCs, these are small airlines and emit less CO_2; and their pollution abatement activities are limited by budget constraints and nature of operations.

5. Concluding remarks

This study employed the Luenberger productivity indicator to derive productivity estimates that credit airlines for undertaking pollution abatement activities. The productivity values for both models are then regressed against environmental variables to explain efficiency drivers.

The two models used in this paper to calculate productivity changes are the market model and the joint model. The joint model shows lower productivity because the productivity estimated by the market model fails to credit airlines for adopting pollution abatement activities. We conclude that in order to capture the true productivity performance, one should consider both good and bad outputs. The productivity estimated by the joint model is more appropriate because, over the period concerned, airlines are actively involved in findings ways to reduce their carbon footprint. The reallocation of resources suggest that productivity measures need to account for the opportunity costs of abatement activities faced by airlines.

We find that most LCCs were more productive than mainstream airlines largely due to efficiency improvements in operations such as adoption of ‘best-practice’ management through improved resource allocation and/or reduction in organizational slack. There seems to be an abundance of evidence which can be drawn from statements made in airline annual reports. However, our analysis also revealed that it is just as important to measure annual technical inefficiency to understand what the contributors to productivity are. From the determinants analysis, LCC dummy contributes positively to productivity only in the market model. Thus, LCC tends to increase productivity compared with mainstream airlines from 2004 to 2010. We observed that most LCCs were ‘catching-up’ which explains the growth rate of efficiency change, whereas for most of the mainstream airlines, technical inefficiency ranged between zero and 0.10 which suggests that mainstream airlines are already operating close to levels of ‘best-practice’ management which explains the insignificant changes in efficiency change.

Policy implications can be drawn from the second stage results. First, *ownership* albeit statistically insignificant, suggests that governments can be more involved in technological adoption through investments or/and improving operations through skills upgrade. As noted, 82 percent of the sample airlines are state-owned suggesting that governments have some stake in ensuring airlines remain viable. Second, *LCC* is statistically significant under $\text{Productivity}_{\text{market}}$ attributed to efficiency change but insignificant under $\text{Productivity}_{\text{joint}}$, suggesting potential productivity improvements if LCCs improve their operations. Third, *demand* and *Age* (the latter being statistically insignificant) for both models negatively impacts on productivity attributed to falling efficiency change. As technical change is statistically insignificant which suggests that airlines are most likely using the latest technology and because airlines face high operational costs, there is very little incentive to upgrade technologies (especially LCCs) unless the current technology is rendered obsolete. But with the current aviation environment focused on reducing carbon emissions, what all these imply is that management will now need to implement operations that not only minimises cost but also mitigates carbon emissions. Hence any improvements can only come from efficiency via better input mix (i.e. workforce becoming more adaptable and efficient in the use of current technology) and/or improvements in airline operations.

References

Adler N, Golany B (2001) Evaluation of deregulated airline networks using data envelopment analysis combined with principal component analysis with an application to Western Europe. European Journal of Operational Research 132:260–273.

Alam IMS, Ross LB, Sickles RC (2001) Time Series Analysis of Strategic Pricing Behavior in the US Airline Industry. Journal of Productivity Analysis 16:49-62.

Assaf AG (2011) A fresh look at the productivity and efficiency changes of UK airlines. Applied Economics 43:2165-2175.

Assaf AG, Josiassen A (2011) The operational performance of UK airlines: 2002-2007. Journal of Economic Studies 38:5-16.

Assaf AG, Josiassen A (2012) European vs. U.S. airlines: Performance comparison in a dynamic market. Tourism Management 33:317-326.

Banker R, Johnston HH (1994) Evaluating the impacts of operating strategies on efficiency in the US Airline Industry. In: Charnes A, Cooper WW, Lewin AY, Seiford LM (eds) Data Envelopment Analysis: Theory, Methodology, and Application. Kluwer Academic Publishers, Boston, pp 97-128.

Barbot C, Costa A, Sochirca E (2008) Airlines performance in the new market context: A comparative productivity and efficiency analysis. Journal of Air Transport Management 14:270-274.

Barros CP, Peypoch N (2009) An evaluation of European airlines' operational performance. International Journal of Production Economics 122:525-533.

Belobaba P, Hernandez K, Jenkins J, Powell R, Swelbar W (2011) Productivity Trends in the US Passenger Airline Industry 1978-2010. Transportation@MIT, http://transportation.mit.edu/sites/default/files/documents/MIT_Air_Passenger_Report.pdf. Accessed 1 June 2015.

Bhadra D (2009) Race to the bottom or swimming upstream: Performance analysis of US airlines. Journal of Air Transport Management 15:227–235.

Bissessur A, Alamdari F (1998) Factors affecting the operational success of strategic airline Alliances. Transportation 25:331–355.

Boussemart, JP, Briec, W, Kerstens, K, Poutineau, JC (2003) Luenberger and Malmquist Productivity Indices: Theoretical Comparisons and Empirical Illustration. Bulletin of Economic Research 55:391-405.

Caves, DW, Christensen, LR, Diewert, WE (1982) The economic theory of index numbers and the measurement of input, output, and productivity. Econometrica 50:1393–1414.

Caves DW, Christensen LR, Tretheway MW (1984) Economies of density versus economies of scale: why trunk and local service airline costs differ. The RAND Journal of Economics 15:471-489.

Chambers RG, Pope RD (1996) Aggregate productivity measures. American Journal of Agricultural Economics. 78:1360–1365.

Chambers RG, Chung YH, Färe R (1998) Profit, directional distance functions, and Nerlovian efficiency. Journal of Optimization Theory and Applications 98:351–364.

Chambers, R.G. (2002) Exact nonradial input, output, and productivity measurement, Economic Theory, 20, 751–65.

Coelli T, Lauwers L, Van Huylenbroeck G (2007) Environmental efficiency measurement and the materials balance condition. Journal of Productivity Analysis 28:3–12.

Coelli T, Perelman S, Romano E (1999) Accounting for Environmental Influences in Stochastic Frontier Models: With Application to International Airlines. Journal of Productivity Analysis 11:251–273.

Dakpo KH, Jeanneaux P, Latruffe L (2016) Modelling Pollution-Generating Technologies in Performance Benchmarking: Recent Developments, Limits and Future Prospects in the Nonparametric Framework. European Journal of Operational Research 250:347-359.

Distexhe V, Perelman S (1994) Technical Efficiency and Productivity Growth in an Era of Deregulation: the Case of Airlines. Swiss Journal of Economics and Statistics 4:669-689.

Färe R, Grosskopf S, Pasurka S (2001) Accounting for Air Pollution Emissions in Measures of State Manufacturing Productivity Growth. Journal of Regional Science 41:381-409.

Färe R, Grosskopf S, Noh D, Weber W (2005) Characteristics of a polluting technology. Journal of Econometrics 126:469–492.

Färe R, Grosskopf S, Pasurka C (2007) Environmental Production Functions and Environmental Directional Distance Functions. Energy 32:1055-1066.

Färe R, Grosskopf S, Sickles RC (2007) Productivity? of US Airlines After Deregulation. Journal of Transport Economics and Policy 41:93-112.

Fujii H, Kaneko S, Managi S (2010) Changes in environmentally sensitive productivity and technological modernization in China's iron and steel industry in the 1990s. Environment and Development Economics 15:485-504.

Fujii H, Managi S, Kawahara H (2011) The Pollution Release and Transfer Register system in the U.S. and Japan: An analysis of productivity. Journal of Cleaner Production 19:1330-1338.

Gillen D, Lall A (1997) Developing measures of air transport productivity and performance: an application of data envelopment analysis. Transportation Research Part E: Logistics and Transportation Review 33:261–273.

Good DH, Nadiri MI, Röller LH, Sickles RC (1993) Efficiency and productivity growth comparisons of European and U.S. Air carriers: A first look at the data. Journal of Productivity Analysis 4:115-125.

Good DH, Röller LH, Sickles RC (1995) Airline efficiency differences between Europe and the US: Implications for the pace of EC integration and domestic Regulation. European Journal of Operational Research 80:508-518.

Greer MR (2006) Are the discount airlines actually more efficient than the legacy carriers?: A Data Envelopment Analysis. International Journal of Transport Economics 33:37-55.

Greer MR (2008) Nothing focuses the mind on productivity quite like the fear of liquidation: Changes in airline productivity in the United States, 2000–2004. Transportation Research Part A: Policy and Practice 42:414-426.

Hoang VN, Coelli T (2011) Measurement of agricultural total factor productivity growth incorporating environmental factors: A nutrients balance approach. Journal of Environmental Economics and Management 62:462–474.

Inglada V, Rey B, Rodríguez-Alvarez A, Coto-Millan P (2006) Liberalisation and efficiency in international air transport. Transportation Research Part A: Policy and Practice. 40:95–105.

Jeon, EM, Sickles, RC (2004) The Role of Environmental Factors in Growth Accounting. Journal of Applied Econometrics 19:567–591.

Koutsomanoli-Filippaki AI, Margaritis D, Staikouras C (2009) Efficiency and Productivity Growth in the Banking Industry of Central and Eastern Europe. Journal of Banking and Finance 33:557-567.

Lee BL, Wilson C, Pasurka C (2015) The Good, the Bad and the Efficient: Productivity, efficiency and technical change in the Airline Industry, 2004-2011. Journal of Transport Economics and Policy 49:338-354.

Managi S, Jena PR (2008) Environmental productivity and Kuznets curve in India. Ecological Economics 65:432-440.

Mendes ML, Santos G (2008) Using economic instruments to address emissions from air transport in the European Union. Environment and Planning A 40:189-209.

O’Donnell, CJ (2010) Measuring and Decomposing Agricultural Productivity and Profitability Change. Australian Journal of Agricultural and Resource Economics 54:527-560.

O’Donnell, CJ (2012) An Aggregate Quantity Framework for Measuring and Decomposing Productivity and Profitability Change. Journal of Productivity Analysis 38:255-272.

Ouellette P, Petit P, Tessier-Parent LP, Vigeant S (2010) Introducing regulation in the measurement of efficiency, with an application to the Canadian air carriers industry. European Journal of Operational Research 200:216–226.

Oum, TH, Yu, C (1998) Winning Airlines: Productivity and Cost Competitiveness of the World's Major Airlines. Springer, New York.

Oum TH, Fu XW, Yu C (2005) New evidences on airline efficiency and yields: a comparative analysis of major North American air carriers and its implications. Transport Policy 12:153–164.

Peyrache, A (2014) Hicks-Moorsteen versus Malmquist: A Connection by Means of a Radial Productivity Index. Journal of Productivity Analysis 41:435-442.

RDC Aviation (2011) RDC Emissions Calculator: Methodology Document (v.1.4).

Scheraga CA (2004) Operational efficiency versus financial mobility in the global airline industry: a data envelopment and Tobit analysis. Transportation Research Part A: Policy and Practice: 38:383–404.

Semenick Alam IM, Sickles RC (1998) The relationship between stock market returns and technical efficiency innovations: evidence from the US Airline Industry. Journal of Productivity Analysis 9:35–51.

Sickles RC, Good DH, Getachew L (2002) Specification of Distance Functions Using Semi- and Nonparametric Methods with an Application to the Dynamic Performance of Eastern and Western European Air Carriers. Journal of Productivity Analysis 17:133–155.

Simar L, Wilson PW (2000) A general methodology for bootstrapping in non-parametric frontier models. Journal of applied statistics 27:779–802.

Tofallis C (1997) Input Efficiency Profiling: An Application to Airlines. Computers Ops Res 24:253-258.

White LJ (1979) Economies of scale and the question of natural monopoly in the airline industry. Journal of Air Law and Commerce 44:545-573.

Yagi M, Fujii H, Hoang V, Managi, S (2015) Environmental efficiency of energy, materials, and emissions. Journal of Environmental Management 161:206-218.

Table 1: Descriptive Statistics for stage one analysis (2004-2010), (in thousands)

		Mean	Standard	Minimum	Maximum
2004	X1- Fuel burn (tonnes)	2 410.4	2 679.8	79.0	10 171.6
	X2- Average aircraft capacity	297.2	97.1	150.5	594.0
	X3- Number of employees	23.1	26.1	0.4	92.7
	X4- Hours flown	805.7	1 082.6	22.8	4 164.5
	Y1- CO_2 (tonnes)	7 609.6	8 460.1	249.4	32 111.9
	Y2- Revenue tonne kms	6 495 060.1	7 609 980.5	109 562.2	27 731 236.3
2005	X1- Fuel burn (tonnes)	2 497.0	2 688.9	96.2	10 216.5
	X2- Average aircraft capacity	307.3	107.5	148.6	704.0
	X3- Number of employees	22.9	25.0	0.5	90.0
	X4- Hours flown	839.6	1 085.1	27.7	4 207.5
	Y1- CO_2 (tonnes)	7 883.2	8 488.9	303.7	32 253.5
	Y2- Revenue tonne kms	6 821 212.7	7 626 166.2	168 017.0	28 981 451.6
2006	X1- Fuel burn (tonnes)	2 551.1	2 633.2	101.6	10 053.9
	X2- Average aircraft capacity	313.8	92.6	140.6	521.9
	X3- Number of employees	23.0	24.6	0.8	93.5
	X4- Hours flown	858.9	1 053.4	29.9	4 145.8
	Y1- CO_2 (tonnes)	8 053.8	8 313.1	320.8	31 740.1
	Y2- Revenue tonne kms	7 199 986.8	7 771 178.0	189 280.2	30 405 658.1
2007	X1- Fuel burn (tonnes)	2 643.1	2 624.5	118.1	9 879.3
	X2- Average aircraft capacity	306.5	85.2	144.2	585.3
	X3- Number of employees	23.9	25.0	0.8	100.8
	X4- Hours flown	892.9	1 053.0	37.9	4 046.6
	Y1- CO_2 (tonnes)	8 344.4	8 285.5	372.7	31 188.9
	Y2- Revenue tonne kms	7 583 768.8	7 978 940.4	327 276.1	31 169 078.2
2008	X1- Fuel burn (tonnes)	2 687.4	2 541.4	108.3	9 406.1
	X2- Average aircraft capacity	301.2	78.0	146.3	511.7
	X3- Number of employees	25.0	26.7	0.8	108.1
	X4- Hours flown	901.1	995.6	41.2	3 826.1
	Y1- CO_2 (tonnes)	8 484.0	8 023.3	341.8	29 695.2
	Y2- Revenue tonne kms	7 647 933.6	7 730 683.6	318 998.2	29 517 613.5
2009	X1- Fuel burn (tonnes)	2 588.5	2 377.1	92.6	8 654.9
	X2- Average aircraft capacity	285.5	75.9	142.1	455.4
	X3- Number of employees	24.5	26.3	0.8	112.3
	X4- Hours flown	868.8	916.1	44.8	3 479.7
	Y1- CO_2 (tonnes)	8 221.4	7 462.9	292.2	27 323.5
	Y2- Revenue tonne kms	7 494 018.6	7 495 841.3	222 891.1	28 654 314.7
2010	X1- Fuel burn (tonnes)	2 761.1	2 704.4	111.6	11 443.6
	X2- Average aircraft capacity	287.6	83.5	158.1	491.1
	X3- Number of employees	25.4	28.1	1.1	117.1
	X4- Hours flown	950.0	1 103.0	61.5	5 107.2
	Y1- CO_2 (tonnes)	8 775.7	8 492.2	352.3	36 127.3
	Y2- Revenue tonne kms	8 139 330.3	8 522 870.1	324 009.1	37 459 975.6

Table 2: Descriptive Statistics for determinants analysis (2004-2010)

		Mean	Standard deviation	Minimum	Maximum
2004	Member	0.41	0.50	0.00	1.00
	LCC	0.38	0.49	0.00	1.00
	Ownership	0.79	0.41	0.00	1.00
	WLF	74.00	5.70	61.70	84.00
	Age	8.96	3.36	3.10	16.40
2005	Member	0.41	0.50	0.00	1.00
	LCC	0.38	0.49	0.00	1.00
	Ownership	0.79	0.41	0.00	1.00
	WLF	75.58	5.43	58.70	84.00
	Age	8.96	3.36	3.10	16.40
2006	Member	0.44	0.50	0.00	1.00
	LCC	0.38	0.49	0.00	1.00
	Ownership	0.82	0.39	0.00	1.00
	WLF	76.76	4.89	63.30	83.70
	Age	8.96	3.36	3.10	16.40
2007	Member	0.44	0.50	0.00	1.00
	LCC	0.38	0.49	0.00	1.00
	Ownership	0.82	0.39	0.00	1.00
	WLF	77.50	4.69	66.00	85.60
	Age	8.96	3.36	3.10	16.40
2008	Member	0.44	0.50	0.00	1.00
	LCC	0.38	0.49	0.00	1.00
	Ownership	0.82	0.39	0.00	1.00
	WLF	76.40	5.76	61.60	86.90
	Age	8.96	3.36	3.10	16.40
2009	Member	0.44	0.50	0.00	1.00
	LCC	0.38	0.49	0.00	1.00
	Ownership	0.82	0.39	0.00	1.00
	WLF	76.72	5.43	63.60	89.20
	Age	8.96	3.36	3.10	16.40
2010	Member	0.47	0.51	0.00	1.00
	LCC	0.38	0.49	0.00	1.00
	Ownership	0.82	0.39	0.00	1.00
	WLF	78.34	4.98	67.10	88.50
	Age	8.96	3.36	3.10	16.40

Table 3: Decomposition of LPI Average Annual Changes, 2004-2010
(Market model: Ignoring bad output CO_2)

Airline name	Nationality	$\text{Productivity}_{\text{market}}$	$\text{EFFCH}_{\text{market}}$	$\text{TECHCH}_{\text{market}}$	Rank
Skymark Airlines (LCC)	Japan	0.178	0.164	0.014	1
GOL (LCC)	Brazil	0.134	0.169	-0.034	2
WestJet (LCC)	Canada	0.131	0.135	-0.004	3
Norwegian (LCC)	Norway	0.114	0.073	0.042	4
Ryanair (LCC)	Rep. of Ireland	0.112	0.093	0.019	5
Southwest Airlines (LCC)	USA	0.108	0.089	0.020	6
TAM	Brazil	0.103	0.126	-0.024	7
Air Asia (LCC)	Malaysia	0.092	0.132	-0.040	8
AirTran Airways (LCC)	USA	0.077	0.075	0.002	9
Garuda Indonesia	Indonesia	0.065	0.092	-0.027	10
Frontier Airlines (LCC)	USA	0.048	0.067	-0.019	11
Emirates	UAE	0.047	0.015	0.033	12
KLM	Netherlands	0.046	0.056	-0.010	13
Delta Airlines	USA	0.045	0.005	0.041	14
Japan Airlines	Japan	0.031	0.030	0.001	15
Virgin Australia (LCC)	Australia	0.030	0.020	0.011	16
Easyjet (LCC)	UK	0.029	0.001	0.028	17
Air Canada	Canada	0.028	0.031	-0.003	18
ANA	Japan	0.027	0.053	-0.025	19
United Airlines	USA	0.022	0.000	0.022	20
Malaysia Airlines	Malaysia	0.021	0.036	-0.016	21
SAS Scandinavian Airlines	Denmark/Norway/Sweden	0.020	0.034	-0.014	22
Singapore Airlines	Singapore	0.015	-0.000	0.015	23
American Airlines	USA	0.014	-0.000	0.014	24
Thai Airways	Thailand	0.013	-0.005	0.018	25
Qantas	Australia	0.013	0.031	-0.018	26
Air France	France	0.013	0.028	-0.016	27
Swiss International Airlines	Switzerland	0.010	-0.007	0.017	28
Aer Lingus	Rep. of Ireland	-0.012	-0.000	-0.012	29
British Airways	UK	-0.020	-0.018	-0.002	30
Germanwings (LCC)	Germany	-0.022	-0.050	0.028	31
Lufthansa	Germany	-0.024	-0.015	-0.009	32
Transavia.com (LCC)	Netherlands	-0.026	0.006	-0.032	33
Philippine Airlines	Philippines	-0.030	-0.013	-0.017	34
All sample average		0.043	0.043	0.000	
LCC airline average		0.077	0.075	0.003	
Mainstream airline average		0.021	0.023	-0.002	
Nonparametric test		***	***		

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Decomposition of LPI Average Annual Changes, 2004-2010
(Joint model: Accounting for bad output CO_2)

Airline name	Nationality	$\text{Productivity}_{\text{joint}}$	$\text{EFFCH}_{\text{joint}}$	$\text{TECHCH}_{\text{joint}}$	Rank
American Airlines	USA	0.105	-0.000	0.105	1
Singapore Airlines	Singapore	0.067	0.000	0.067	2
Skymark Airlines (LCC)	Japan	0.062	0.066	-0.005	3
Ryanair (LCC)	Rep. of Ireland	0.060	0.040	0.020	4
Emirates	UAE	0.042	0.009	0.033	5
TAM	Brazil	0.041	0.048	-0.007	6
WestJet (LCC)	Canada	0.039	0.046	-0.007	7
Norwegian (LCC)	Norway	0.038	0.029	0.008	8
Southwest Airlines (LCC)	USA	0.036	0.036	0.000	9
GOL (LCC)	Brazil	0.030	0.040	-0.010	10
Air Asia (LCC)	Malaysia	0.028	0.052	-0.024	11
Garuda Indonesia	Indonesia	0.025	0.034	-0.009	12
AirTran Airways (LCC)	USA	0.021	0.027	-0.006	13
KLM	Netherlands	0.021	0.029	-0.007	14
United Airlines	USA	0.018	0.000	0.018	15
Japan Airlines	Japan	0.015	0.020	-0.005	16
Delta Airlines	USA	0.014	0.005	0.010	17
Air Canada	Canada	0.012	0.014	-0.002	18
ANA	Japan	0.010	0.018	-0.008	19
Malaysia Airlines	Malaysia	0.010	0.019	-0.010	20
SAS Scandinavian Airlines	Denmark/Norway/Sweden	0.008	0.013	-0.005	21
Qantas	Australia	0.007	0.013	-0.007	22
Air France	France	0.007	0.013	-0.006	23
Swiss International Airline	Switzerland	0.005	-0.003	0.008	24
Thai Airways	Thailand	0.004	-0.002	0.006	25
Frontier Airlines (LCC)	USA	0.001	0.011	-0.010	26
Germanwings (LCC)	Germany	-0.008	-0.022	0.014	27
Aer Lingus	Rep. of Ireland	-0.011	0.000	-0.011	28
Lufthansa	Germany	-0.015	-0.008	-0.006	29
Virgin Australia (LCC)	Australia	-0.015	-0.005	-0.010	30
Transavia.com (LCC)	Netherlands	-0.016	-0.003	-0.013	31
Philippine Airlines	Philippines	-0.017	-0.007	-0.010	32
British Airways	UK	-0.017	-0.015	-0.002	33
Easyjet (LCC)	UK	-0.029	0.002	-0.031	34
All sample average		0.018	0.015	0.002	
LCC airline average		0.019	0.025	-0.006	
Mainstream airline average		0.017	0.010	0.007	
Nonparametric test			*		

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Technical inefficiency scores derived from market model, 2004-2010

Airline name	2004	2005	2006	2007	2008	2009	2010
Skymark Airlines (LCC)	1.240	0.623	0.929	0.276	0.267	0.494	0.255
GOL (LCC)	1.570	1.217	0.915	0.834	0.904	0.649	0.557
WestJet (LCC)	1.077	0.391	0.355	0.297	0.272	0.284	0.265
Norwegian (LCC)	0.701	0.420	0.419	0.641	0.405	0.286	0.265
Ryanair (LCC)	0.560	0.173	0.178	0.115	0.095	0.039	**0.000**
Southwest Airlines (LCC)	0.881	0.388	0.401	0.374	0.317	0.355	0.349
TAM	0.774	0.549	0.269	0.219	0.174	0.207	0.017
Air Asia (LCC)	0.896	0.542	0.535	0.348	0.358	0.322	0.105
AirTran Airways (LCC)	0.921	0.624	0.633	0.541	0.476	0.442	0.474
Garuda Indonesia	0.674	0.390	0.262	0.325	0.335	0.259	0.124
Frontier Airlines (LCC)	0.824	0.518	0.569	0.492	0.463	0.389	0.420
Emirates	0.087	0.125	0.033	**0.000**	**0.000**	**0.000**	**0.000**
KLM	0.335	0.080	0.135	0.310	0.269	0.012	**0.000**
Delta Airlines	0.029	0.026	0.004	**0.000**	**0.000**	**0.000**	**0.000**
Japan Airlines	0.233	0.155	0.157	0.138	0.176	0.255	0.052
Virgin Australia (LCC)	0.455	0.450	0.438	0.465	0.564	0.406	0.337
Easyjet (LCC)	0.040	**0.000**	0.046	0.015	**0.000**	**0.000**	0.032
Air Canada	0.226	0.032	0.057	0.079	0.050	0.061	0.040
ANA	0.597	0.334	0.363	0.345	0.344	0.271	0.281
United Airlines	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Malaysia Airlines	0.307	0.123	0.230	0.171	0.199	0.072	0.089
SAS Scandinavian Airlines	0.417	0.223	0.220	0.181	0.325	0.403	0.211
Singapore Airlines	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
American Airlines	**0.000**	**0.000**	**0.000**	**0.000**	0.003	**0.000**	0.001
Thai Airways	0.030	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.060
Qantas	0.224	**0.000**	**0.000**	**0.000**	0.015	**0.000**	0.040
Air France	0.170	0.111	0.112	0.058	0.051	0.021	**0.000**
Swiss International Airlines	0.101	0.051	0.151	0.078	0.052	0.110	0.141
Aer Lingus	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
British Airways	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.108
Germanwings (LCC)	0.045	0.016	0.106	0.097	0.205	0.321	0.345
Lufthansa	0.032	0.218	0.269	0.194	0.157	0.198	0.123
Transavia.com (LCC)	0.322	0.356	0.462	0.231	0.251	0.385	0.287
Philippine Airlines	0.000	0.252	0.243	0.233	0.190	0.137	0.077
All sample average	0.405	0.247	0.250	0.208	0.203	0.188	0.149
LCC airline average	0.733	0.440	0.461	0.364	0.352	0.336	0.284
Mainstream airline average	0.202	0.127	0.119	0.111	0.111	0.096	0.065
Nonparametric test	***	***	***	***	***	***	***

Note: Score shows inefficiency of operation estimated by market model. Score equal zero shows airline achieved efficient performance and consisted frontier line. Number is highlighted if score equal zero.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Technical inefficiency scores derived from joint model, 2004-2010

Airline name	2004	2005	2006	2007	2008	2009	2010
American Airlines	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Singapore Airlines	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Skymark Airlines (LCC)	0.510	0.313	0.350	0.161	0.118	0.198	0.113
Ryanair (LCC)	0.240	0.084	0.086	0.060	0.053	0.025	**0.000**
Emirates	0.056	0.068	0.019	**0.000**	**0.000**	**0.000**	**0.000**
TAM	0.296	0.224	0.123	0.103	0.091	0.110	0.009
WestJet (LCC)	0.406	0.180	0.170	0.136	0.138	0.139	0.131
Norwegian (LCC)	0.382	0.222	0.234	0.289	0.217	0.223	0.205
Southwest Airlines (LCC)	0.380	0.189	0.191	0.194	0.165	0.173	0.163
GOL (LCC)	0.465	0.378	0.318	0.315	0.322	0.247	0.226
Air Asia (LCC)	0.309	0.213	0.211	0.148	0.152	0.227	**0.000**
Garuda Indonesia	0.268	0.174	0.123	0.150	0.160	0.136	0.063
AirTran Airways (LCC)	0.362	0.257	0.269	0.225	0.215	0.203	0.198
KLM	0.172	0.046	0.072	0.147	0.128	0.007	**0.000**
United Airlines	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Japan Airlines	0.146	0.074	0.080	0.070	0.088	0.127	0.027
Delta Airlines	0.029	**0.000**	0.002	**0.000**	**0.000**	**0.000**	**0.000**
Air Canada	0.103	0.017	0.030	0.038	0.028	0.032	0.020
ANA	0.242	0.146	0.157	0.151	0.163	0.137	0.131
Malaysia Airlines	0.161	0.069	0.123	0.089	0.098	0.039	0.045
SAS Scandinavian Airlines	0.177	0.102	0.101	0.085	0.142	0.168	0.097
Qantas	0.102	**0.000**	**0.000**	**0.000**	0.008	**0.000**	0.021
Air France	0.079	0.059	0.056	0.030	0.027	0.013	**0.000**
Swiss International Airlines	0.063	0.030	0.085	0.046	0.036	0.068	0.079
Thai Airways	0.020	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.031
Frontier Airlines (LCC)	0.322	0.221	0.242	0.210	0.195	0.262	0.258
Germanwings (LCC)	0.032	0.000	0.062	0.058	0.137	0.167	0.165
Aer Lingus	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Lufthansa	0.016	0.102	0.125	0.092	0.081	0.109	0.065
Virgin Australia (LCC)	0.276	0.221	0.216	0.227	0.232	0.306	0.305
Transavia.com (LCC)	0.139	0.151	0.188	0.104	0.112	0.194	0.155
Philippine Airlines	**0.000**	0.123	0.126	0.121	0.103	0.076	0.041
British Airways	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.089
Easyjet (LCC)	0.026	**0.000**	0.028	0.009	**0.000**	**0.000**	0.017
All sample average	0.170	0.108	0.111	0.096	0.094	0.100	0.078
LCC airline average	0.296	0.187	0.197	0.164	0.158	0.182	0.149
Mainstream airline average	0.092	0.059	0.058	0.053	0.055	0.049	0.034
Nonparametric test	***	**	***	**	**	***	**

Note: Score shows inefficiency of operation estimated by market model. Score equal zero shows airline achieved efficient performance and consisted frontier line. Number is highlighted if score equal zero.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7 Productivity determinants for LPI estimated by market model

	Productivity$_{market}$			EFFCH$_{market}$			TECHCH$_{market}$		
Variable	Coefficient	z-value	sig	Coefficient	z-value	sig	Coefficient	z-value	sig
Constant	0.602	4.310	***	0.746	5.790	***	-0.144	-2.010	**
Member	0.026	1.310		0.030	1.760	*	-0.004	-0.340	
LCC	0.059	2.900	***	0.049	2.550	**	0.010	0.920	
Ownership	0.016	1.060		0.028	1.720	*	-0.011	-1.390	
Demand	-0.007	-4.050	***	-0.009	-5.440	***	0.002	1.970	**
Age	-0.004	-1.430		-0.006	-2.520	**	0.002	0.940	
# of sample	204			204			204		
R-square:									
within	0.102			0.100			0.001		
between	0.467			0.579			0.235		
overall	0.145			0.168			0.024		

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8 Productivity determinants for LPI estimated by joint model

	Productivity$_{joint}$			EFFCH$_{joint}$			TECHCH$_{joint}$		
Variable	Coefficient	z-value	sig	Coefficient	z-value	sig	Coefficient	z-value	sig
Constant	0.256	3.900	***	0.296	5.470	***	-0.041	-0.960	
Member	0.020	1.500		0.011	1.450		0.009	0.760	
LCC	0.015	1.380		0.013	1.620		0.003	0.370	
Ownership	-0.003	-0.250		0.011	1.720	*	-0.014	-1.170	
Demand	-0.003	-3.250	***	-0.004	-4.940	***	0.001	0.750	
Age	-0.001	-0.500		-0.002	-2.240	**	0.001	0.620	
# of sample	204			204			204		
R-square:									
within	0.082			0.129			0.000		
between	0.058			0.452			0.170		
overall	0.048			0.154			0.021		

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix 1. Luenberger indicator estimated from Joint model with 1,000 times bootstrap estimation

Airline name	2004-2005		2005-2006		2006-2007		2007-2008		2008-2009		2009-2010	
Aer Lingus	-0.0642***	(-0.0667, -0.0618)	0.0505***	(0.0483, 0.0528)	0.0203***	(0.0098, 0.0308)	0.0154***	(0.0084, 0.0224)	-0.2232***	(-0.3002, -0.1462)	0.0386	(-0.0891, 0.1662)
Air Asia (LCC)	0.0233***	(0.0216, 0.0249)	0.0314***	(0.0294, 0.0334)	0.0577***	(0.0559, 0.0596)	-0.0173***	(-0.0186, -0.0161)	-0.0917***	(-0.0926, -0.0908)	0.5399***	(0.4672, 0.6126)
Air Canada	0.0412***	(0.0378, 0.0446)	0.0079***	(0.0066, 0.0091)	0.0074***	(0.007, 0.0078)	-0.0008***	(-0.0009, -0.0006)	0.0134***	(0.0129, 0.0139)	0.0245***	(0.0204, 0.0286)
Air France	-0.0372***	(-0.0387, -0.0357)	0.0335***	(0.0318, 0.0352)	0.0839***	(0.0273, 0.1406)	0.054**	(0.0061, 0.1019)	0.0155***	(0.0145, 0.0165)	0.0197***	(0.0144, 0.025)
AirTran Airways (LCC)	0.0449***	(0.0439, 0.0459)	0.0137***	(0.0125, 0.0148)	0.0407***	(0.0398, 0.0416)	0.0206***	(0.0197, 0.0215)	0.0086***	(0.0079, 0.0094)	-0.0053***	(-0.006, -0.0046)
American Airlines	0.1691***	(0.1421, 0.1961)	0.0191**	(0.0036, 0.0346)	0.0878	(-0.0654, 0.241)	-0.0159*	(-0.0322, 0.0004)	0.0284***	(0.02, 0.0369)	-0.034***	(-0.0572, -0.0107)
ANA	0.0439***	(0.0438, 0.044)	0.0135***	(0.0135, 0.0136)	-0.0022***	(-0.0023, -0.0021)	-0.0115***	(-0.0116, -0.0114)	0.0216***	(0.0216, 0.0217)	-0.0032***	(-0.0032, -0.0032)
British Airways	-0.0132	(-0.0508, 0.0245)	-0.0168	(-0.0864, 0.0528)	0.098***	(0.0829, 0.113)	-3.0758***	(-3.6657, -2.4859)	0.0074***	(0.0026, 0.0122)	-0.0164**	(-0.0324, -0.0004)
Delta Airlines	0.2037***	(0.0647, 0.3427)	0.0697***	(0.0447, 0.0948)	0.0421**	(0.0019, 0.0823)	0.0008	(-0.0201, 0.0217)	0.0334	(-0.0444, 0.1111)	0.1979*	(-0.0007, 0.3965)
Easyjet (LCC)	0.0592***	(0.0499, 0.0685)	-0.0006	(-0.0083, 0.0071)	0.0222***	(0.0173, 0.0272)	0.1147***	(0.1025, 0.127)	-0.0523***	(-0.0788, -0.0259)	-0.0411***	(-0.0723, -0.0099)
Emirates	-0.0364*	(-0.0778, 0.0051)	0.5099***	(0.1326, 0.8872)	0.0479	(-0.0828, 0.1787)	0.053**	(0.006, 0.1001)	-0.1174***	(-0.2054, -0.0293)	0.0699***	(0.0256, 0.1143)
Frontier Airlines (LCC)	0.0223***	(0.021, 0.0236)	0.0072***	(0.0056, 0.0088)	0.0301***	(0.0287, 0.0315)	0.0174***	(0.0163, 0.0185)	-0.0824***	(-0.0833, -0.0816)	0.0028***	(0.0016, 0.004)
Garuda Indonesia	0.0311***	(0.0301, 0.032)	0.0828***	(0.0822, 0.0835)	-0.0272***	(-0.0276, -0.0268)	-0.0068***	(-0.0072, -0.0064)	0.0176***	(0.017, 0.0181)	0.0583***	(0.0567, 0.0599)
Germanwings (LCC)	-0.3144	(-0.7211, 0.0922)	-0.0149	(-0.0614, 0.0316)	-0.0151*	(-0.0305, 0.0002)	-0.0397***	(-0.0432, -0.0363)	-0.0554***	(-0.0573, -0.0536)	0.017***	(0.0159, 0.0181)
GOL (LCC)	0.022***	(0.0203, 0.0237)	0.0859***	(0.0839, 0.0879)	-0.0042***	(-0.0058, -0.0027)	-0.009***	(-0.0102, -0.0079)	0.0621***	(0.0611, 0.0631)	0.0135***	(0.0125, 0.0145)
Japan Airlines	0.0571***	(0.0544, 0.0599)	0.0028**	(0, 0.0056)	-0.002**	(-0.0037, -0.0003)	-0.0444***	(-0.0492, -0.0396)	-0.0484***	(-0.0493, -0.0476)	0.1054***	(0.104, 0.1068)
KLM	0.0982***	(0.0886, 0.1079)	-0.0024***	(-0.004, -0.0007)	-0.0905***	(-0.0916, -0.0893)	0.0014***	(0.0006, 0.0021)	0.1154***	(0.1087, 0.1221)	0.078***	(0.0513, 0.1048)
Lufthansa	-0.1427***	(-0.1433, -0.1421)	0.0032***	(0.0032, 0.0032)	0.0254***	(0.0251, 0.0256)	0.0146***	(0.0143, 0.015)	-0.0212***	(-0.0247, -0.0178)	0.046***	(0.0439, 0.0481)
Malaysia Airlines	0.0415***	(0.0362, 0.0467)	-0.0275***	(-0.032, -0.0229)	0.1935***	(0.0982, 0.2888)	-0.0549***	(-0.0742, -0.0356)	0.0461***	(0.0461, 0.0462)	0.0016***	(0.0014, 0.0017)
Norwegian (LCC)	0.1947***	(0.1387, 0.2506)	-0.0259	(-0.0783, 0.0264)	-0.0485***	(-0.0506, -0.0463)	0.0761***	(0.0745, 0.0778)	0.0282*	(-0.0041, 0.0606)	0.1925***	(0.1007, 0.2844)
Philippine Airlines	-0.1494***	(-0.151, -0.1479)	0.013***	(0.0119, 0.0142)	0.0029***	(0.0017, 0.0041)	0.0062***	(0.0047, 0.0077)	-0.0005	(-0.0012, 0.0002)	0.0312***	(0.0305, 0.0319)
Qantas	0.0184	(-0.0682, 0.105)	0.0852***	(0.0459, 0.1245)	-0.0153***	(-0.0232, -0.0075)	-0.0221**	(-0.0409, -0.0033)	-0.0032	(-0.0087, 0.0024)	-0.0213***	(-0.0322, -0.0104)
Ryanair (LCC)	0.078***	(0.077, 0.0791)	0.0269***	(0.0257, 0.0282)	0.0287***	(0.0277, 0.0298)	0.0972***	(0.0714, 0.1231)	0.0626***	(0.0518, 0.0733)	0.1981***	(0.1791, 0.217)
SAS Scandinavian Airlines	0.0248***	(0.0242, 0.0254)	0.0256***	(0.0249, 0.0264)	0.008***	(0.0076, 0.0085)	-0.0338***	(-0.0347, -0.033)	-0.0237***	(-0.0245, -0.0228)	0.0462***	(0.0457, 0.0467)
Singapore Airlines	0.055	(-0.0605, 0.1705)	-1.0032**	(-1.9731, -0.0333)	0.4529	(-0.2193, 1.1251)	-0.1517***	(-0.2392, -0.0642)	-0.0267	(-0.1518, 0.0983)	1.2309	(-0.6649, 3.1267)
Skymark Airlines (LCC)	0.1608***	(0.1585, 0.1632)	-0.005***	(-0.0076, -0.0025)	0.2941***	(0.1062, 0.4819)	0.025***	(0.023, 0.027)	-0.1098***	(-0.1109, -0.1088)	0.0906***	(0.0893, 0.0919)
Southwest Airlines (LCC)	0.2372***	(0.2115, 0.263)	0.0182***	(0.0153, 0.0212)	0.0247***	(0.0211, 0.0284)	0.014***	(0.0116, 0.0164)	0.0149***	(0.012, 0.0177)	0.0127***	(0.01, 0.0154)
Swiss International Airline	0.0273***	(0.0245, 0.03)	0.0203*	(-0.0017, 0.0424)	0.1845**	(0.0362, 0.3328)	0.1634*	(-0.0264, 0.3533)	-0.038***	(-0.0581, -0.0179)	0.8459	(-0.8179, 2.5098)
TAM	0.009***	(0.0081, 0.01)	0.1261***	(0.125, 0.1272)	0.0134***	(0.0126, 0.0142)	0.0289***	(0.028, 0.0298)	-0.0175***	(-0.0182, -0.0167)	0.084***	(0.0795, 0.0885)
Thai Airways	0.1061***	(0.1009, 0.1113)	-0.0013	(-0.0093, 0.0066)	0.0115**	(0.0023, 0.0208)	-0.028	(-0.0617, 0.0057)	0.0149	(-0.057, 0.0868)	-0.0124***	(-0.0167, -0.0081)
Transavia.com (LCC)	-0.0901***	(-0.0917, -0.0885)	-0.0094***	(-0.0113, -0.0075)	0.0797***	(0.0778, 0.0815)	-0.0224***	(-0.0237, -0.0211)	-0.101***	(-0.1017, -0.1002)	0.0448***	(0.0435, 0.046)
United Airlines	0.0482**	(0.0078, 0.0886)	0.0522***	(0.026, 0.0785)	0.001	(-0.0209, 0.0228)	0.048*	(-0.0086, 0.1047)	-0.0045	(-0.0413, 0.0323)	-0.1536	(-0.3495, 0.0424)
Virgin Australia (LCC)	-0.0048***	(-0.007, -0.0027)	0.0363***	(0.0342, 0.0383)	-0.0078***	(-0.0097, -0.0059)	-0.0186***	(-0.02, -0.0173)	-0.0873***	(-0.0884, -0.0861)	0.0002	(-0.0025, 0.0029)
WestJet (LCC)	0.157***	(0.1549, 0.1591)	0.0379***	(0.0365, 0.0394)	0.0308***	(0.0294, 0.0321)	0.0064***	(0.0053, 0.0075)	-0.01***	(-0.0109, -0.0091)	0.0012***	(0.0005, 0.0019)

Note1: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.
Note2: Figures in parenthesis represent estimated 95% confidence intervals.

Appendix 2. Efficiency change indicator estimated from Joint model with 1,000 times bootstrap estimation

Airline name	2004-2005		2005-2006		2006-2007		2007-2008		2008-2009		2009-2010	
Aer Lingus	-0.0123***	(-0.0142, -0.0104)	0.009***	(0.0081, 0.0099)	-0.0022	(-0.0056, 0.0012)	-0.0014	(-0.0057, 0.0029)	0.3116***	(0.2304, 0.3927)	-0.0665	(-0.1588, 0.0258)
Air Asia (LCC)	0.0843***	(0.0832, 0.0854)	0.009***	(0.0083, 0.0098)	0.0614***	(0.0609, 0.0618)	-0.016***	(-0.0171, -0.0149)	-0.0831***	(-0.0842, -0.0821)	0.4196***	(0.361, 0.4782)
Air Canada	0.0661***	(0.0634, 0.0687)	-0.0142***	(-0.0149, -0.0134)	-0.0071***	(-0.0078, -0.0064)	0.0124***	(0.0116, 0.0133)	-0.0008	(-0.0037, 0.0021)	0.009***	(0.0066, 0.0115)
Air France	0.0094***	(0.0066, 0.0123)	0.0057***	(0.0045, 0.0068)	0.1502***	(0.0385, 0.2618)	-0.1282**	(-0.2397, -0.0166)	0.0093***	(0.0084, 0.0103)	0.0241***	(0.0139, 0.0343)
AirTran Airways (LCC)	0.0903***	(0.089, 0.0916)	-0.0065***	(-0.007, -0.0059)	0.037***	(0.0363, 0.0377)	0.0141***	(0.0133, 0.0149)	0.0068***	(0.0062, 0.0073)	0.0027***	(0.0023, 0.003)
American Airlines	0.1683***	(0.1451, 0.1915)	-0.1635***	(-0.1875, -0.1395)	0.0554***	(0.0322, 0.0786)	-0.0532***	(-0.0747, -0.0316)	-0.0001	(-0.0068, 0.0066)	0.0219***	(0.0091, 0.0348)
ANA	0.0827***	(0.081, 0.0845)	-0.0027***	(-0.0033, -0.002)	-0.0003	(-0.0009, 0.0003)	-0.0095***	(-0.0103, -0.0088)	0.0212***	(0.0208, 0.0216)	0.0022***	(0.0018, 0.0027)
British Airways	-0.0849***	(-0.1358, -0.034)	-0.0072	(-0.0408, 0.0264)	-0.041***	(-0.0569, -0.0251)	0.1005***	(0.0747, 0.1263)	-0.1038***	(-0.1323, -0.0753)	-0.0477**	(-0.0906, -0.0048)
Delta Airlines	0.0285***	(0.0206, 0.0364)	0.0189*	(-0.0019, 0.0397)	0.0311	(-0.0117, 0.0738)	-0.0296	(-0.067, 0.0078)	0.1266***	(0.0632, 0.1901)	-0.0571*	(-0.1231, 0.0089)
Easyjet (LCC)	0.0287***	(0.0174, 0.0399)	-0.0489***	(-0.0583, -0.0396)	0.0058*	(-0.0003, 0.012)	0.0398***	(0.0267, 0.053)	0.1534***	(0.1111, 0.1957)	-0.151***	(-0.1925, -0.1095)
Emirates	0.0548***	(0.015, 0.0947)	0.133***	(0.0699, 0.196)	-0.138***	(-0.2102, -0.0659)	0.0303	(-0.0456, 0.1062)	-0.0262	(-0.1131, 0.0608)	0.0054	(-0.0581, 0.0689)
Frontier Airlines (LCC)	0.0843***	(0.0827, 0.0859)	-0.0162***	(-0.0168, -0.0157)	0.0277***	(0.0272, 0.0283)	0.0103***	(0.0095, 0.0111)	-0.0765***	(-0.0772, -0.0758)	0.0121***	(0.0113, 0.0129)
Garuda Indonesia	0.0805***	(0.0793, 0.0817)	0.0592***	(0.0581, 0.0604)	-0.0288***	(-0.0294, -0.0283)	-0.0086***	(-0.0093, -0.0079)	0.0181***	(0.0173, 0.019)	0.0693***	(0.0662, 0.0725)
Germanwings (LCC)	-0.7822	(-1.7369, 0.1724)	-0.0242	(-0.0808, 0.0324)	-0.0765**	(-0.1364, -0.0166)	-0.0686***	(-0.0725, -0.0647)	-0.0455***	(-0.0492, -0.0419)	0.0069***	(0.006, 0.0078)
GOL (LCC)	0.0773***	(0.0764, 0.0783)	0.0666***	(0.066, 0.0673)	-0.0026***	(-0.0032, -0.0019)	-0.0152***	(-0.0162, -0.0142)	0.0669***	(0.0661, 0.0676)	0.0265***	(0.0257, 0.0273)
Japan Airlines	0.0624***	(0.0594, 0.0653)	-0.0056***	(-0.0071, -0.004)	0.0009	(-0.0013, 0.003)	-0.0235***	(-0.0245, -0.0225)	-0.0404***	(-0.0419, -0.0389)	0.0981***	(0.0957, 0.1005)
KLM	0.1128***	(0.109, 0.1166)	-0.0237***	(-0.0257, -0.0218)	-0.0882***	(-0.0899, -0.0865)	0.0153***	(0.0146, 0.0161)	0.1189***	(0.1178, 0.12)	0.043***	(0.0374, 0.0485)
Lufthansa	-0.0917***	(-0.0942, -0.0893)	-0.0183***	(-0.0191, -0.0176)	0.026***	(0.0252, 0.0268)	0.0156***	(0.0147, 0.0166)	-0.031***	(-0.0316, -0.0304)	0.0454***	(0.0442, 0.0465)
Malaysia Airlines	0.0712***	(0.0605, 0.0819)	-0.0548***	(-0.0651, -0.0446)	0.033***	(0.0306, 0.0353)	-0.0186***	(-0.0209, -0.0163)	0.0544***	(0.0537, 0.055)	-0.0048***	(-0.0053, -0.0043)
Norwegian (LCC)	0.2786***	(0.1677, 0.3894)	-0.1353**	(-0.2461, -0.0246)	-0.0549***	(-0.0559, -0.0539)	0.068***	(0.0661, 0.0698)	-0.009***	(-0.0116, -0.0064)	0.0626***	(0.055, 0.0702)
Philippine Airlines	-0.105***	(-0.1069, -0.1031)	-0.0055***	(-0.0062, -0.0048)	0.0066***	(0.0061, 0.0071)	0.0189***	(0.0181, 0.0196)	0.0154***	(0.0145, 0.0163)	0.0311***	(0.0303, 0.0318)
Qantas	-0.0014	(-0.1745, 0.1716)	0.0054***	(0.0029, 0.0078)	-0.0026	(-0.0147, 0.0095)	-0.0255***	(-0.0374, -0.0136)	0.0035***	(0.0022, 0.0048)	-0.0183***	(-0.0212, -0.0155)
Ryanair (LCC)	0.1381***	(0.1365, 0.1397)	0.0044***	(0.0038, 0.005)	0.0207***	(0.0198, 0.0216)	0.0143***	(0.0116, 0.017)	0.1031***	(0.0838, 0.1223)	0.1025***	(0.0713, 0.1338)
SAS Scandinavian Airlines	0.0638***	(0.0622, 0.0654)	0.0095***	(0.0088, 0.0102)	0.0084***	(0.0076, 0.0091)	-0.0475***	(-0.0485, -0.0465)	-0.031***	(-0.0314, -0.0306)	0.0665***	(0.0656, 0.0674)
Singapore Airlines	0.1481**	(0.0167, 0.2795)	-0.0006	(-0.1544, 0.1532)	-0.0062	(-0.1262, 0.1139)	-0.2104**	(-0.3782, -0.0426)	0.0734	(-0.0988, 0.2455)	1.7792	(-1.9505, 5.5088)
Skymark Airlines (LCC)	0.1924***	(0.1896, 0.1951)	-0.0373***	(-0.0398, -0.0348)	0.1986***	(0.1976, 0.1996)	0.0333***	(0.0322, 0.0344)	-0.1012***	(-0.1031, -0.0993)	0.0969***	(0.0959, 0.098)
Southwest Airlines (LCC)	0.1765***	(0.1729, 0.1801)	-0.0069***	(-0.0082, -0.0056)	0.0014***	(0.0006, 0.0023)	0.0368***	(0.0339, 0.0397)	-0.0106***	(-0.013, -0.0082)	-0.0016	(-0.0058, 0.0025)
Swiss International Airline	0.0204***	(0.0095, 0.0313)	0.0066	(-0.0699, 0.083)	0.2376	(-0.0662, 0.5414)	-0.2383	(-0.5321, 0.0555)	0.0215	(-0.0131, 0.0562)	1.6467	(-1.6831, 4.9764)
TAM	0.0593***	(0.0581, 0.0605)	0.1077***	(0.1071, 0.1083)	0.0133***	(0.0128, 0.0139)	0.0195***	(0.0187, 0.0204)	-0.0255***	(-0.026, -0.0249)	0.0957***	(0.091, 0.1004)
Thai Airways	0.0417***	(0.0362, 0.0473)	0.0063	(-0.0059, 0.0185)	-0.0168***	(-0.0291, -0.0046)	0.0304	(-0.0072, 0.068)	-0.0496**	(-0.089, -0.0102)	-0.0417***	(-0.0487, -0.0347)
Transavia.com (LCC)	-0.0273***	(-0.0287, -0.0259)	-0.0319***	(-0.0325, -0.0313)	0.084***	(0.0836, 0.0845)	-0.0208***	(-0.0221, -0.0196)	-0.094***	(-0.095, -0.093)	0.0517***	(0.0505, 0.0529)
United Airlines	-0.1128**	(-0.2093, -0.0163)	-0.0725**	(-0.1437, -0.0014)	-0.0067	(-0.0393, 0.026)	0.114***	(0.0417, 0.1864)	-0.0582	(-0.1305, 0.0142)	0.02	(-0.0126, 0.0526)
Virgin Australia (LCC)	0.0465***	(0.0451, 0.048)	0.0106***	(0.0101, 0.011)	-0.0144***	(-0.0147, -0.014)	-0.0165***	(-0.0176, -0.0155)	-0.0789***	(-0.0805, -0.0773)	0.0211***	(0.0164, 0.0259)
WestJet (LCC)	0.2128***	(0.2108, 0.2148)	0.014***	(0.0136, 0.0144)	0.0254***	(0.0248, 0.026)	0.0014***	(0.0007, 0.0021)	-0.0095***	(-0.0102, -0.0089)	0.0056***	(0.005, 0.0061)

Note1: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.
Note2: Figures in parenthesis represent estimated 95% confidence intervals.

Appendix 3. Technical change indicator estimated from Joint model with 1,000 times bootstrap estimation

Airline name	2004-2005		2005-2006		2006-2007		2007-2008		2008-2009		2009-2010	
Aer Lingus	-0.0519***	(-0.0544, -0.0495)	0.0415***	(0.0393, 0.0438)	0.0224***	(0.0119, 0.0329)	0.0168***	(0.0098, 0.0238)	-0.5348***	(-0.6111, -0.4585)	0.1051	(-0.0244, 0.2345)
Air Asia (LCC)	-0.061***	(-0.0634, -0.0586)	0.0223***	(0.0207, 0.024)	-0.0036***	(-0.0056, -0.0017)	-0.0013	(-0.0033, 0.0007)	-0.0086***	(-0.01, -0.0072)	0.1203***	(0.0484, 0.1922)
Air Canada	-0.0248***	(-0.0293, -0.0204)	0.022***	(0.0206, 0.0234)	0.0145***	(0.0138, 0.0153)	-0.0132***	(-0.0141, -0.0123)	0.0142***	(0.0115, 0.0169)	0.0154***	(0.0106, 0.0203)
Air France	-0.0466***	(-0.0494, -0.0439)	0.0278***	(0.0257, 0.0299)	-0.0662**	(-0.1225, -0.01)	0.1822**	(0.0227, 0.3416)	0.0062***	(0.0048, 0.0075)	-0.0044	(-0.0098, 0.0009)
AirTran Airways (LCC)	-0.0454***	(-0.0472, -0.0436)	0.0201***	(0.0191, 0.0212)	0.0037***	(0.0026, 0.0048)	0.0065***	(0.0054, 0.0075)	0.0019***	(0.0009, 0.0028)	-0.008***	(-0.0088, -0.0072)
American Airlines	0.0009	(-0.0266, 0.0283)	0.1826***	(0.1664, 0.1987)	0.0324	(-0.1204, 0.1852)	0.0373***	(0.0206, 0.054)	0.0285***	(0.0202, 0.0369)	-0.0559***	(-0.0791, -0.0328)
ANA	-0.0388***	(-0.0406, -0.0371)	0.0162***	(0.0155, 0.0169)	-0.0019***	(-0.0025, -0.0013)	-0.002***	(-0.0026, -0.0013)	0.0005**	(0.0001, 0.0009)	-0.0054***	(-0.0059, -0.005)
British Airways	0.0717***	(0.0278, 0.1156)	-0.0096	(-0.0828, 0.0636)	0.139***	(0.1156, 0.1623)	-3.1763***	(-3.7676, -2.585)	0.1112***	(0.083, 0.1393)	0.0313*	(-0.0018, 0.0644)
Delta Airlines	0.1752**	(0.036, 0.3143)	0.0509***	(0.0257, 0.076)	0.0111	(-0.0291, 0.0513)	0.0304***	(0.0095, 0.0513)	-0.0932**	(-0.1784, -0.0081)	0.255**	(0.0566, 0.4533)
Easyjet (LCC)	0.0305***	(0.0211, 0.04)	0.0484***	(0.0413, 0.0554)	0.0164***	(0.0118, 0.021)	0.0749***	(0.0626, 0.0873)	-0.2058***	(-0.2324, -0.1791)	0.1099***	(0.0792, 0.1406)
Emirates	-0.0912***	(-0.1325, -0.0499)	0.3769**	(0.0011, 0.7528)	0.186***	(0.056, 0.316)	0.0228	(-0.0242, 0.0697)	-0.0912**	(-0.1794, -0.003)	0.0645***	(0.0203, 0.1087)
Frontier Airlines (LCC)	-0.062***	(-0.0645, -0.0595)	0.0234***	(0.0219, 0.0249)	0.0023***	(0.0007, 0.004)	0.0071***	(0.0056, 0.0086)	-0.0059***	(-0.0071, -0.0047)	-0.0093***	(-0.0104, -0.0082)
Garuda Indonesia	-0.0494***	(-0.0503, -0.0485)	0.0236***	(0.0229, 0.0242)	0.0016***	(0.0012, 0.002)	0.0018***	(0.0014, 0.0022)	-0.0006**	(-0.0011, -0.0001)	-0.011***	(-0.0126, -0.0094)
Germanwings (LCC)	0.4678*	(-0.0808, 1.0164)	0.0093	(-0.0374, 0.056)	0.0614***	(0.0166, 0.1061)	0.0289***	(0.0252, 0.0326)	-0.0099***	(-0.0129, -0.0069)	0.0101***	(0.0089, 0.0113)
GOL (LCC)	-0.0553***	(-0.0576, -0.0531)	0.0192***	(0.0175, 0.021)	-0.0017*	(-0.0035, 0.0002)	0.0061***	(0.0044, 0.0078)	-0.0047***	(-0.006, -0.0034)	-0.013***	(-0.0141, -0.0119)
Japan Airlines	-0.0053***	(-0.0081, -0.0024)	0.0084***	(0.0056, 0.0112)	-0.0029***	(-0.0047, -0.0011)	-0.0209***	(-0.0256, -0.0161)	-0.008***	(-0.0089, -0.0072)	0.0073***	(0.0059, 0.0087)
KLM	-0.0146***	(-0.0249, -0.0043)	0.0214***	(0.0193, 0.0235)	-0.0023***	(-0.0038, -0.0008)	-0.014***	(-0.015, -0.0129)	-0.0036	(-0.0103, 0.0032)	0.035**	(0.0084, 0.0617)
Lufthansa	-0.051***	(-0.0534, -0.0485)	0.0216***	(0.0209, 0.0223)	-0.0006	(-0.0014, 0.0002)	-0.001**	(-0.0019, -0.0001)	0.0098***	(0.0064, 0.0131)	0.0007	(-0.0018, 0.0032)
Malaysia Airlines	-0.0297***	(-0.0361, -0.0233)	0.0274***	(0.0215, 0.0332)	0.1605***	(0.0656, 0.2555)	-0.0363***	(-0.0551, -0.0175)	-0.0082***	(-0.0088, -0.0076)	0.0064***	(0.0058, 0.0069)
Norwegian (LCC)	-0.0839***	(-0.1388, -0.029)	0.1094***	(0.0509, 0.1679)	0.0064***	(0.0048, 0.0081)	0.0082***	(0.0065, 0.0099)	0.0373**	(0.0049, 0.0697)	0.1299***	(0.0377, 0.2221)
Philippine Airlines	-0.0444***	(-0.046, -0.0428)	0.0185***	(0.0173, 0.0197)	-0.0037***	(-0.0049, -0.0026)	-0.0127***	(-0.0139, -0.0114)	-0.0159***	(-0.0173, -0.0145)	0.0002	(-0.0008, 0.0011)
Qantas	0.0198	(-0.0668, 0.1065)	0.0798***	(0.0404, 0.1192)	-0.0127***	(-0.0206, -0.0049)	0.0034	(-0.0154, 0.0222)	-0.0067**	(-0.0122, -0.0011)	-0.003	(-0.0139, 0.0079)
Ryanair (LCC)	-0.0601***	(-0.0623, -0.0578)	0.0225***	(0.0214, 0.0237)	0.008***	(0.0068, 0.0093)	0.0829***	(0.0573, 0.1084)	-0.0405***	(-0.0511, -0.0298)	0.0955***	(0.0717, 0.1194)
SAS Scandinavian Airlines	-0.039***	(-0.0406, -0.0374)	0.0161***	(0.0154, 0.0168)	-0.0003	(-0.0013, 0.0006)	0.0136***	(0.0127, 0.0145)	0.0074***	(0.0064, 0.0083)	-0.0203***	(-0.0213, -0.0193)
Singapore Airlines	-0.0931	(-0.2106, 0.0244)	-1.0026**	(-1.9429, -0.0622)	0.4591	(-0.2179, 1.1361)	0.0587	(-0.029, 0.1464)	-0.1001	(-0.239, 0.0388)	-0.5483	(-2.4537, 1.3572)
Skymark Airlines (LCC)	-0.0315***	(-0.0341, -0.029)	0.0323***	(0.0302, 0.0343)	0.0954	(-0.0924, 0.2833)	-0.0083***	(-0.0106, -0.006)	-0.0086***	(-0.0105, -0.0067)	-0.0063***	(-0.0074, -0.0052)
Southwest Airlines (LCC)	0.0608***	(0.0353, 0.0862)	0.0252***	(0.0223, 0.0281)	0.0233***	(0.0197, 0.0269)	-0.0228***	(-0.0252, -0.0203)	0.0255***	(0.0226, 0.0284)	0.0143***	(0.0117, 0.017)
Swiss International Airline	0.0069	(-0.0035, 0.0173)	0.0138	(-0.0437, 0.0712)	-0.0531	(-0.2109, 0.1047)	0.4017***	(0.1964, 0.6071)	-0.0595***	(-0.0928, -0.0263)	-0.8007	(-2.4669, 0.8655)
TAM	-0.0502***	(-0.0519, -0.0485)	0.0184***	(0.0174, 0.0194)	0.0001	(-0.001, 0.0011)	0.0094***	(0.0084, 0.0103)	0.008***	(0.0071, 0.0089)	-0.0117***	(-0.0149, -0.0084)
Thai Airways	0.0644***	(0.0591, 0.0697)	-0.0077*	(-0.0157, 0.0004)	0.0284***	(0.019, 0.0377)	-0.0584***	(-0.0919, -0.0249)	0.0645*	(-0.0071, 0.1361)	0.0293***	(0.0247, 0.0339)
Transavia.com (LCC)	-0.0628***	(-0.0654, -0.0602)	0.0225***	(0.0208, 0.0241)	-0.0043***	(-0.0063, -0.0024)	-0.0015	(-0.0036, 0.0005)	-0.007***	(-0.0084, -0.0055)	-0.0069***	(-0.0081, -0.0058)
United Airlines	0.161***	(0.0987, 0.2233)	0.1248***	(0.063, 0.1866)	0.0076	(-0.0199, 0.0352)	-0.066***	(-0.107, -0.025)	0.0537**	(0.0114, 0.0959)	-0.1736*	(-0.3695, 0.0224)
Virgin Australia (LCC)	-0.0514***	(-0.054, -0.0487)	0.0257***	(0.0239, 0.0275)	0.0066***	(0.0045, 0.0086)	-0.0021**	(-0.0041, -0.0001)	-0.0083***	(-0.0098, -0.0069)	-0.0209***	(-0.0235, -0.0183)
WestJet (LCC)	-0.0557***	(-0.0579, -0.0536)	0.0239***	(0.0225, 0.0254)	0.0053***	(0.004, 0.0067)	0.005***	(0.0039, 0.0062)	-0.0004	(-0.0014, 0.0005)	-0.0044***	(-0.0051, -0.0036)

Note1: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Note2: Figures in parenthesis represent estimated 95% confidence intervals.

Appendix 4. Luenberger indicator estimated from Market model with 1,000 times bootstrap estimation

Airline name	2004-2005		2005-2006		2006-2007		2007-2008		2008-2009		2009-2010	
Aer Lingus	-0.1033***	(-0.108, -0.0985)	0.0671***	(0.0624, 0.0719)	0.0047*	(-0.0006, 0.01)	-0.0029	(-0.0073, 0.0015)	-0.0401***	(-0.044, -0.0362)	-0.0037**	(-0.0071, -0.0003)
Air Asia (LCC)	0.0937***	(0.086, 0.1014)	0.1009***	(0.0949, 0.1068)	0.1552***	(0.1495, 0.1609)	-0.043***	(-0.0474, -0.0385)	-0.015***	(-0.0182, -0.0117)	0.2266***	(0.2232, 0.2299)
Air Canada	0.0923***	(0.091, 0.0935)	0.009***	(0.0084, 0.0096)	0.013***	(0.013, 0.0131)	-0.0009***	(-0.001, -0.0008)	0.0235***	(0.0233, 0.0236)	0.0283***	(0.0281, 0.0284)
Air France	-0.0696***	(-0.0737, -0.0655)	0.0624***	(0.0595, 0.0653)	0.0398***	(0.0374, 0.0423)	-0.001	(-0.0027, 0.0006)	0.0257***	(0.0243, 0.027)	0.0221***	(0.021, 0.0232)
AirTran Airways (LCC)	0.1603***	(0.1556, 0.165)	0.0475***	(0.0443, 0.0507)	0.1281***	(0.1251, 0.1311)	0.0732***	(0.0705, 0.0758)	0.0226***	(0.0202, 0.0251)	-0.0151***	(-0.0171, -0.0131)
American Airlines	0.0375***	(0.029, 0.046)	0.0228***	(0.014, 0.0317)	-0.0117***	(-0.0191, -0.0042)	-0.0256***	(-0.0332, -0.0181)	0.0224***	(0.015, 0.0298)	0.0061*	(-0.0006, 0.0129)
ANA	0.1154***	(0.1148, 0.116)	0.0349***	(0.0347, 0.035)	-0.0058***	(-0.006, -0.0056)	-0.0292***	(-0.0293, -0.0291)	0.0521***	(0.0519, 0.0523)	-0.0075***	(-0.0075, -0.0074)
British Airways	-0.1625***	(-0.1635, -0.1615)	0.0168***	(0.0165, 0.0172)	0.0797***	(0.0793, 0.08)	-0.0052***	(-0.0055, -0.0049)	0.0059***	(0.0054, 0.0065)	-0.0465***	(-0.0468, -0.0462)
Delta Airlines	0.0489***	(0.0425, 0.0553)	0.0512***	(0.0455, 0.057)	0.0293***	(0.0242, 0.0344)	0.1296***	(0.1222, 0.137)	-0.0602***	(-0.0679, -0.0525)	0.0885***	(0.0809, 0.096)
Easyjet (LCC)	0.0638***	(0.0602, 0.0674)	0.0022	(-0.0009, 0.0053)	0.0336***	(0.0313, 0.0359)	0.097***	(0.0938, 0.1001)	-0.0148***	(-0.0178, -0.0118)	-0.0033**	(-0.0059, -0.0006)
Emirates	-0.0325***	(-0.0387, -0.0262)	0.1409***	(0.1343, 0.1475)	0.0414***	(0.0348, 0.0479)	0.0421***	(0.0361, 0.0481)	-0.0124***	(-0.0182, -0.0066)	0.1041***	(0.0977, 0.1106)
Frontier Airlines (LCC)	0.0838***	(0.0776, 0.09)	0.0296***	(0.025, 0.0342)	0.0867***	(0.0819, 0.0914)	0.042***	(0.0386, 0.0454)	0.0377***	(0.035, 0.0404)	-0.0403***	(-0.043, -0.0375)
Garuda Indonesia	0.0915***	(0.0911, 0.0919)	0.2014***	(0.2009, 0.2019)	-0.0623***	(-0.0625, -0.0621)	-0.013***	(-0.0135, -0.0126)	0.0417***	(0.0411, 0.0424)	0.1172***	(0.1167, 0.1177)
Germanwings (LCC)	0.0734***	(0.0693, 0.0775)	-0.0184***	(-0.0234, -0.0134)	-0.002	(-0.0071, 0.0032)	-0.08***	(-0.0839, -0.0761)	-0.1366***	(-0.1402, -0.133)	0.0371***	(0.0337, 0.0405)
GOL (LCC)	0.0527***	(0.0408, 0.0647)	0.3911***	(0.3817, 0.4004)	0.0337***	(0.0265, 0.0409)	-0.0362***	(-0.0407, -0.0317)	0.2245***	(0.2203, 0.2287)	0.0427***	(0.0397, 0.0458)
Japan Airlines	0.1056***	(0.1015, 0.1096)	0.0131***	(0.0097, 0.0165)	0.0014	(-0.0008, 0.0037)	-0.0775***	(-0.0796, -0.0754)	-0.1121***	(-0.1135, -0.1106)	0.2255***	(0.2243, 0.2268)
KLM	0.1794***	(0.175, 0.1838)	-0.0032**	(-0.006, -0.0004)	-0.1833***	(-0.1862, -0.1804)	0.0076***	(0.0051, 0.0101)	0.2135***	(0.2116, 0.2154)	0.0541***	(0.0524, 0.0558)
Lufthansa	-0.2825***	(-0.2837, -0.2812)	0.0074***	(0.0073, 0.0074)	0.0622***	(0.0617, 0.0628)	0.0456***	(0.0448, 0.0463)	-0.028***	(-0.029, -0.0271)	0.0827***	(0.0823, 0.0831)
Malaysia Airlines	0.0805***	(0.0801, 0.0809)	-0.0467***	(-0.0472, -0.0462)	0.0528***	(0.0522, 0.0534)	-0.0654***	(-0.0667, -0.0642)	0.0905***	(0.0899, 0.0911)	0.0027***	(0.0026, 0.0029)
Norwegian (LCC)	0.2896***	(0.2853, 0.2939)	0.0697***	(0.066, 0.0735)	-0.1931***	(-0.1971, -0.1891)	0.2849***	(0.2801, 0.2897)	0.085***	(0.0818, 0.0882)	0.1216***	(0.1178, 0.1255)
Philippine Airlines	-0.2718***	(-0.2745, -0.2692)	0.0277***	(0.0249, 0.0306)	0.0045***	(0.002, 0.007)	0.0152***	(0.012, 0.0184)	-0.0036**	(-0.0064, -0.0007)	0.0575***	(0.0559, 0.0592)
Qantas	0.1112***	(0.1109, 0.1116)	0.0627***	(0.0622, 0.0632)	-0.0236***	(-0.0238, -0.0234)	-0.0497***	(-0.0498, -0.0495)	-0.0018***	(-0.002, -0.0017)	-0.0249***	(-0.025, -0.0247)
Ryanair (LCC)	0.1961***	(0.1912, 0.2009)	0.0599***	(0.0567, 0.0631)	0.0629***	(0.06, 0.0658)	0.0498***	(0.0473, 0.0522)	0.0457***	(0.0429, 0.0485)	0.2667***	(0.2608, 0.2725)
SAS Scandinavian Airlines	0.0685***	(0.0653, 0.0718)	0.0613***	(0.0593, 0.0632)	0.0186***	(0.0167, 0.0205)	-0.0803***	(-0.0826, -0.078)	-0.0636***	(-0.0662, -0.0609)	0.1197***	(0.1175, 0.122)
Singapore Airlines	0.0309***	(0.0198, 0.042)	0.0567***	(0.0451, 0.0683)	-0.0011	(-0.0116, 0.0094)	-0.0436***	(-0.0532, -0.034)	0.0189***	(0.0101, 0.0277)	0.0115***	(0.0031, 0.0199)
Skymark Airlines (LCC)	0.576***	(0.5664, 0.5857)	-0.2155***	(-0.2238, -0.2072)	0.6229***	(0.616, 0.6298)	0.017***	(0.012, 0.022)	-0.2862***	(-0.2905, -0.2818)	0.2421***	(0.2389, 0.2452)
Southwest Airlines (LCC)	0.4698***	(0.4634, 0.4762)	0.0531***	(0.0491, 0.0572)	0.0525***	(0.0482, 0.0568)	0.0212***	(0.0166, 0.0258)	0.0157***	(0.0115, 0.0198)	0.0242***	(0.0195, 0.029)
Swiss International Airline	0.0274***	(0.0271, 0.0278)	-0.0218***	(-0.0234, -0.0202)	0.0919***	(0.0898, 0.0941)	0.0328***	(0.0313, 0.0343)	-0.0575***	(-0.0578, -0.0572)	0.0183***	(0.0181, 0.0184)
TAM	0.035***	(0.0302, 0.0399)	0.3379***	(0.3348, 0.341)	0.0317***	(0.0292, 0.0342)	0.0659***	(0.0636, 0.0682)	-0.037***	(-0.039, -0.035)	0.1499***	(0.1487, 0.1511)
Thai Airways	0.1698***	(0.169, 0.1706)	-0.0049***	(-0.0052, -0.0045)	0.0087***	(0.0082, 0.0093)	-0.0332***	(-0.0334, -0.0329)	-0.0548***	(-0.0551, -0.0544)	-0.0142***	(-0.0145, -0.014)
Transavia.com (LCC)	-0.2146***	(-0.2206, -0.2086)	-0.0245***	(-0.0297, -0.0192)	0.2033***	(0.198, 0.2085)	-0.0528***	(-0.0571, -0.0485)	-0.1764***	(-0.1796, -0.1732)	0.1097***	(0.1066, 0.1129)
United Airlines	0.0494***	(0.0439, 0.0548)	0.0296***	(0.0244, 0.0348)	0.0037	(-0.0012, 0.0085)	-0.0233***	(-0.0285, -0.0181)	0.0056**	(0.0008, 0.0104)	0.0624***	(0.0557, 0.0691)
Virgin Australia (LCC)	-0.0281***	(-0.0324, -0.0237)	0.1038***	(0.099, 0.1087)	-0.0074***	(-0.0121, -0.0028)	-0.0685***	(-0.0736, -0.0634)	0.1148***	(0.1106, 0.119)	0.0329***	(0.0304, 0.0354)
WestJet (LCC)	0.5353***	(0.5297, 0.5409)	0.093***	(0.089, 0.097)	0.0757***	(0.072, 0.0794)	0.0213***	(0.0183, 0.0243)	-0.0228***	(-0.0251, -0.0205)	0.0247***	(0.0228, 0.0267)

Note1: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Note2: Figures in parenthesis represent estimated 95% confidence intervals.

Appendix 5. Efficiency change indicator estimated from Market model with 1,000 times bootstrap estimation

Airline name	2004-2005		2005-2006		2006-2007		2007-2008		2008-2009		2009-2010	
Aer Lingus	-0.0193***	(-0.0269, -0.0116)	0.0111***	(0.0042, 0.018)	-0.0048	(-0.0124, 0.0029)	-0.0049	(-0.0113, 0.0015)	-0.0147***	(-0.0196, -0.0098)	-0.0033	(-0.0084, 0.0017)
Air Asia (LCC)	0.2922***	(0.2828, 0.3017)	0.0271***	(0.022, 0.0322)	0.1618***	(0.1565, 0.1671)	-0.0333***	(-0.0378, -0.0288)	0.0105***	(0.0074, 0.0137)	0.226***	(0.2217, 0.2304)
Air Canada	0.1446***	(0.1388, 0.1504)	-0.0264***	(-0.0274, -0.0254)	-0.0153***	(-0.0164, -0.0141)	0.0278***	(0.0263, 0.0293)	-0.0077***	(-0.0088, -0.0066)	0.0124***	(0.0105, 0.0142)
Air France	0.0346***	(0.0288, 0.0403)	0.0076***	(0.0036, 0.0115)	0.0374***	(0.0338, 0.041)	0.0039***	(0.0016, 0.0063)	0.018***	(0.0162, 0.0198)	0.0184***	(0.0169, 0.02)
AirTran Airways (LCC)	0.2499***	(0.2438, 0.2559)	-0.0111***	(-0.0143, -0.0079)	0.088***	(0.0845, 0.0915)	0.0639***	(0.0606, 0.0673)	0.018***	(0.0149, 0.0211)	-0.0229***	(-0.0253, -0.0206)
American Airlines	0.0337***	(0.0218, 0.0457)	-0.0027	(-0.0157, 0.0103)	-0.0132***	(-0.023, -0.0034)	-0.0464***	(-0.0578, -0.0351)	0.0118**	(0.0013, 0.0222)	-0.0268***	(-0.0366, -0.017)
ANA	0.2006***	(0.1937, 0.2075)	-0.0062***	(-0.008, -0.0043)	0.0023***	(0.0008, 0.0038)	-0.0054***	(-0.0072, -0.0037)	0.0629***	(0.0619, 0.064)	-0.0115***	(-0.0124, -0.0105)
British Airways	-0.0625***	(-0.0679, -0.0571)	-0.018***	(-0.0197, -0.0164)	0.0308***	(0.028, 0.0336)	-0.004***	(-0.005, -0.003)	-0.0168***	(-0.0185, -0.0151)	-0.0803***	(-0.0838, -0.0767)
Delta Airlines	-0.0032	(-0.0116, 0.0051)	0.0149***	(0.0068, 0.023)	0.0071*	(-0.0003, 0.0144)	0.0859***	(0.0741, 0.0977)	-0.0269***	(-0.038, -0.0157)	0.0072	(-0.0056, 0.0199)
Easyjet (LCC)	0.0272***	(0.0223, 0.0322)	-0.0344***	(-0.039, -0.0299)	0.0121***	(0.009, 0.0152)	0.0398***	(0.0354, 0.0443)	-0.0176***	(-0.0219, -0.0133)	-0.0298***	(-0.0337, -0.0259)
Emirates	-0.0151***	(-0.0236, -0.0067)	0.0716***	(0.0627, 0.0805)	0.0186***	(0.0093, 0.028)	0.0294***	(0.0214, 0.0374)	-0.0271***	(-0.0362, -0.0179)	0.0374***	(0.028, 0.0467)
Frontier Airlines (LCC)	0.2386***	(0.2292, 0.2479)	-0.0382***	(-0.0436, -0.0328)	0.0611***	(0.0548, 0.0674)	0.0236***	(0.0202, 0.0269)	0.049***	(0.0469, 0.0512)	-0.0191***	(-0.0219, -0.0163)
Garuda Indonesia	0.2214***	(0.216, 0.2269)	0.1436***	(0.142, 0.1452)	-0.0683***	(-0.0692, -0.0673)	-0.0078***	(-0.009, -0.0065)	0.0527***	(0.0511, 0.0544)	0.1236***	(0.1225, 0.1247)
Germanwings (LCC)	0.0174***	(0.0136, 0.0212)	-0.0598***	(-0.066, -0.0535)	0.0002	(-0.0064, 0.0068)	-0.1109***	(-0.117, -0.1049)	-0.1259***	(-0.1307, -0.1211)	-0.0035	(-0.008, 0.0011)
GOL (LCC)	0.3042***	(0.2889, 0.3194)	0.3007***	(0.2887, 0.3128)	0.0359***	(0.0272, 0.0447)	-0.0624***	(-0.0671, -0.0577)	0.219***	(0.2144, 0.2236)	0.0891***	(0.0856, 0.0925)
Japan Airlines	0.0756***	(0.0704, 0.0809)	-0.0081***	(-0.0129, -0.0032)	0.0053***	(0.0027, 0.0078)	-0.0476***	(-0.0504, -0.0449)	-0.0898***	(-0.0919, -0.0877)	0.2079***	(0.2067, 0.2091)
KLM	0.221***	(0.2145, 0.2275)	-0.0451***	(-0.0489, -0.0413)	-0.1879***	(-0.192, -0.1838)	0.039***	(0.0355, 0.0424)	0.2325***	(0.2297, 0.2353)	0.0208***	(0.0185, 0.0231)
Lufthansa	-0.1766***	(-0.181, -0.1721)	-0.045***	(-0.0464, -0.0436)	0.0588***	(0.0568, 0.0608)	0.044***	(0.0416, 0.0463)	-0.0493***	(-0.0505, -0.0482)	0.0763***	(0.0744, 0.0781)
Malaysia Airlines	0.1421***	(0.1358, 0.1485)	-0.0924***	(-0.0939, -0.0909)	0.0454***	(0.0437, 0.0471)	-0.0357***	(-0.0373, -0.0342)	0.1111***	(0.1094, 0.1128)	-0.0141***	(-0.0151, -0.0131)
Norwegian (LCC)	0.2676***	(0.262, 0.2732)	0.0101***	(0.0051, 0.015)	-0.218***	(-0.2228, -0.2131)	0.2327***	(0.2269, 0.2384)	0.0967***	(0.093, 0.1005)	0.055***	(0.0494, 0.0606)
Philippine Airlines	-0.2041***	(-0.208, -0.2002)	-0.0051***	(-0.0083, -0.002)	0.0122***	(0.0096, 0.0148)	0.0442***	(0.0398, 0.0486)	0.0303***	(0.0263, 0.0343)	0.0538***	(0.0515, 0.0562)
Qantas	0.1823***	(0.1755, 0.1892)	0.0118***	(0.0107, 0.013)	-0.0194***	(-0.0212, -0.0177)	-0.0247***	(-0.0266, -0.0227)	0.0055***	(0.0045, 0.0066)	-0.0325***	(-0.0337, -0.0314)
Ryanair (LCC)	0.3341***	(0.3273, 0.3409)	0.0102***	(0.006, 0.0145)	0.0464***	(0.0424, 0.0503)	0.0266***	(0.023, 0.0301)	0.0443***	(0.0405, 0.0481)	0.1285***	(0.1176, 0.1395)
SAS Scandinavian Airlines	0.1638***	(0.1596, 0.168)	0.0229***	(0.0205, 0.0252)	0.0199***	(0.0173, 0.0226)	-0.1143***	(-0.1173, -0.1113)	-0.0889***	(-0.0918, -0.086)	0.1741***	(0.1712, 0.1771)
Singapore Airlines	0.0172**	(0.0012, 0.0332)	-0.0103	(-0.0264, 0.0057)	-0.0094	(-0.0234, 0.0046)	-0.0158**	(-0.029, -0.0026)	0.0025	(-0.0097, 0.0147)	-0.0236***	(-0.0353, -0.0118)
Skymark Airlines (LCC)	0.5948***	(0.5819, 0.6077)	-0.3161***	(-0.3285, -0.3037)	0.6089***	(0.5997, 0.6182)	0.0056	(-0.0013, 0.0124)	-0.2586***	(-0.2632, -0.254)	0.2432***	(0.2401, 0.2464)
Southwest Airlines (LCC)	0.4213***	(0.4123, 0.4302)	-0.0189***	(-0.0237, -0.0141)	0.0348***	(0.0294, 0.0403)	0.0544***	(0.0479, 0.0608)	-0.0343***	(-0.0386, -0.03)	0.0009	(-0.0053, 0.0071)
Swiss International Airline	0.0257***	(0.0233, 0.0282)	-0.0756***	(-0.0782, -0.073)	0.0652***	(0.063, 0.0673)	0.0202***	(0.0188, 0.0216)	-0.0491***	(-0.0509, -0.0473)	-0.026***	(-0.0292, -0.0229)
TAM	0.1678***	(0.1614, 0.1741)	0.2857***	(0.2826, 0.2888)	0.0338***	(0.0309, 0.0366)	0.0531***	(0.05, 0.0562)	-0.0479***	(-0.0507, -0.0452)	0.1745***	(0.1727, 0.1763)
Thai Airways	0.0721***	(0.0672, 0.077)	-0.0232***	(-0.0255, -0.0208)	-0.0072***	(-0.0083, -0.0062)	-0.0097***	(-0.0116, -0.0078)	-0.0095***	(-0.0116, -0.0075)	-0.0428***	(-0.0448, -0.0407)
Transavia.com (LCC)	-0.061***	(-0.0675, -0.0545)	-0.0901***	(-0.0946, -0.0855)	0.2141***	(0.2094, 0.2188)	-0.0442***	(-0.0486, -0.0399)	-0.158***	(-0.1611, -0.1548)	0.1214***	(0.1181, 0.1248)
United Airlines	0.0005	(-0.0078, 0.0088)	-0.0105***	(-0.0172, -0.0039)	-0.0086***	(-0.0144, -0.0027)	0.0295***	(0.0216, 0.0375)	-0.0095***	(-0.0161, -0.0029)	-0.011**	(-0.0206, -0.0015)
Virgin Australia (LCC)	-0.005*	(-0.0109, 0.0009)	0.0286***	(0.0229, 0.0344)	-0.04***	(-0.0461, -0.0338)	-0.0887***	(-0.0953, -0.0822)	0.1304***	(0.125, 0.1357)	0.053***	(0.05, 0.0561)
WestJet (LCC)	0.6393***	(0.632, 0.6466)	0.0349***	(0.0302, 0.0397)	0.0498***	(0.0449, 0.0546)	0.0224***	(0.0186, 0.0263)	-0.0246***	(-0.0278, -0.0215)	0.0156***	(0.013, 0.0182)

Note1: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Note2: Figures in parenthesis represent estimated 95% confidence intervals.

Appendix 6. Technical change indicator estimated from Market model with 1,000 times bootstrap estimation

Airline name	2004-2005		2005-2006		2006-2007		2007-2008		2008-2009		2009-2010	
Aer Lingus	-0.084***	(-0.0888, -0.0792)	0.056***	(0.051, 0.061)	0.0095***	(0.0043, 0.0146)	0.002	(-0.0026, 0.0066)	-0.0254***	(-0.0293, -0.0216)	-0.0004	(-0.0037, 0.003)
Air Asia (LCC)	-0.1985***	(-0.2067, -0.1904)	0.0738***	(0.0677, 0.0798)	-0.0066**	(-0.0124, -0.0007)	-0.0097***	(-0.0145, -0.0049)	-0.0255***	(-0.0288, -0.0222)	0.0006	(-0.0027, 0.0038)
Air Canada	-0.0523***	(-0.0573, -0.0473)	0.0354***	(0.0342, 0.0366)	0.0283***	(0.0272, 0.0294)	-0.0287***	(-0.0302, -0.0272)	0.0311***	(0.03, 0.0323)	0.0159***	(0.014, 0.0178)
Air France	-0.1042***	(-0.1084, -0.0999)	0.0548***	(0.0521, 0.0576)	0.0024*	(-0.0002, 0.005)	-0.005***	(-0.0066, -0.0033)	0.0077***	(0.0062, 0.0091)	0.0037***	(0.0026, 0.0047)
AirTran Airways (LCC)	-0.0895***	(-0.0939, -0.0851)	0.0586***	(0.0556, 0.0616)	0.0401***	(0.0371, 0.0432)	0.0092***	(0.0066, 0.0119)	0.0046***	(0.0021, 0.0072)	0.0078***	(0.0058, 0.0099)
American Airlines	0.0038	(-0.0045, 0.0121)	0.0255***	(0.0163, 0.0347)	0.0016	(-0.0057, 0.0089)	0.0208***	(0.013, 0.0286)	0.0107***	(0.0036, 0.0178)	0.0329***	(0.0258, 0.04)
ANA	-0.0852***	(-0.0918, -0.0785)	0.041***	(0.0391, 0.043)	-0.0081***	(-0.0096, -0.0066)	-0.0238***	(-0.0255, -0.0221)	-0.0108***	(-0.0119, -0.0098)	0.004***	(0.0031, 0.0049)
British Airways	-0.1***	(-0.1062, -0.0937)	0.0349***	(0.0332, 0.0365)	0.0488***	(0.0463, 0.0513)	-0.0012**	(-0.0024, -0.0001)	0.0227***	(0.0213, 0.0241)	0.0338***	(0.0301, 0.0374)
Delta Airlines	0.0522***	(0.0458, 0.0585)	0.0363***	(0.0305, 0.0421)	0.0223***	(0.0173, 0.0272)	0.0437***	(0.0367, 0.0506)	-0.0333***	(-0.0416, -0.025)	0.0813***	(0.0737, 0.0889)
Easyjet (LCC)	0.0366***	(0.0332, 0.04)	0.0367***	(0.0335, 0.0398)	0.0215***	(0.0193, 0.0238)	0.0572***	(0.0541, 0.0602)	0.0027*	(-0.0003, 0.0057)	0.0266***	(0.0239, 0.0292)
Emirates	-0.0173***	(-0.0233, -0.0114)	0.0693***	(0.0627, 0.0759)	0.0227***	(0.0162, 0.0293)	0.0127***	(0.0069, 0.0185)	0.0147***	(0.0088, 0.0206)	0.0668***	(0.0601, 0.0735)
Frontier Airlines (LCC)	-0.1548***	(-0.1613, -0.1483)	0.0678***	(0.0631, 0.0725)	0.0256***	(0.0209, 0.0302)	0.0184***	(0.015, 0.0219)	-0.0113***	(-0.0141, -0.0085)	-0.0211***	(-0.0238, -0.0184)
Garuda Indonesia	-0.1299***	(-0.1351, -0.1247)	0.0578***	(0.0562, 0.0594)	0.0059***	(0.005, 0.0069)	-0.0053***	(-0.0063, -0.0043)	-0.011***	(-0.0122, -0.0098)	-0.0064***	(-0.0072, -0.0056)
Germanwings (LCC)	0.056***	(0.0518, 0.0602)	0.0414***	(0.0365, 0.0463)	-0.0022	(-0.0072, 0.0028)	0.0309***	(0.0271, 0.0347)	-0.0107***	(-0.0144, -0.007)	0.0405***	(0.0371, 0.0439)
GOL (LCC)	-0.2515***	(-0.2644, -0.2386)	0.0904***	(0.0807, 0.1)	-0.0023	(-0.0093, 0.0048)	0.0262***	(0.0216, 0.0308)	0.0055***	(0.0014, 0.0096)	-0.0463***	(-0.0494, -0.0433)
Japan Airlines	0.0299***	(0.0258, 0.034)	0.0212***	(0.0179, 0.0245)	-0.0038***	(-0.0062, -0.0015)	-0.0299***	(-0.0318, -0.0279)	-0.0223***	(-0.0237, -0.0208)	0.0176***	(0.0164, 0.0188)
KLM	-0.0416***	(-0.046, -0.0372)	0.0419***	(0.0392, 0.0446)	0.0046***	(0.0016, 0.0076)	-0.0314***	(-0.0339, -0.0288)	-0.019***	(-0.0209, -0.017)	0.0333***	(0.0317, 0.0348)
Lufthansa	-0.1059***	(-0.1107, -0.1011)	0.0524***	(0.0509, 0.0538)	0.0034***	(0.0018, 0.0051)	0.0016	(-0.0004, 0.0036)	0.0213***	(0.0204, 0.0222)	0.0065***	(0.0046, 0.0083)
Malaysia Airlines	-0.0616***	(-0.0676, -0.0556)	0.0457***	(0.0441, 0.0473)	0.0074***	(0.0061, 0.0087)	-0.0297***	(-0.0313, -0.0281)	-0.0206***	(-0.0219, -0.0192)	0.0169***	(0.0157, 0.018)
Norwegian (LCC)	0.022***	(0.0176, 0.0264)	0.0597***	(0.0559, 0.0634)	0.0249***	(0.0208, 0.0289)	0.0522***	(0.0477, 0.0568)	-0.0117***	(-0.0149, -0.0085)	0.0666***	(0.0628, 0.0705)
Philippine Airlines	-0.0678***	(-0.0705, -0.0651)	0.0329***	(0.0301, 0.0356)	-0.0077***	(-0.0102, -0.0053)	-0.029***	(-0.0324, -0.0256)	-0.0338***	(-0.0366, -0.0311)	0.0037***	(0.002, 0.0054)
Qantas	-0.0711***	(-0.0776, -0.0646)	0.0509***	(0.0494, 0.0524)	-0.0042***	(-0.0059, -0.0025)	-0.025***	(-0.027, -0.023)	-0.0074***	(-0.0085, -0.0062)	0.0077***	(0.0065, 0.0089)
Ryanair (LCC)	-0.138***	(-0.1427, -0.1333)	0.0497***	(0.0465, 0.0529)	0.0165***	(0.0136, 0.0194)	0.0232***	(0.0207, 0.0257)	0.0014	(-0.0014, 0.0042)	0.1381***	(0.1322, 0.144)
SAS Scandinavian Airlines	-0.0952***	(-0.0984, -0.092)	0.0384***	(0.0365, 0.0403)	-0.0013	(-0.0033, 0.0007)	0.034***	(0.0317, 0.0362)	0.0254***	(0.0226, 0.0281)	-0.0544***	(-0.0565, -0.0522)
Singapore Airlines	0.0137**	(0.0029, 0.0245)	0.067***	(0.0551, 0.0789)	0.0083	(-0.0021, 0.0188)	-0.0278***	(-0.0374, -0.0182)	0.0164***	(0.0076, 0.0252)	0.035***	(0.0262, 0.0439)
Skymark Airlines (LCC)	-0.0188***	(-0.0282, -0.0094)	0.1006***	(0.0921, 0.109)	0.014***	(0.0071, 0.0208)	0.0114***	(0.0061, 0.0167)	-0.0276***	(-0.0318, -0.0234)	-0.0012	(-0.0045, 0.0021)
Southwest Airlines (LCC)	0.0485***	(0.0419, 0.0552)	0.072***	(0.0681, 0.0759)	0.0177***	(0.0133, 0.022)	-0.0332***	(-0.0379, -0.0284)	0.05***	(0.0459, 0.0542)	0.0233***	(0.0188, 0.0278)
Swiss International Airline	0.0017	(-0.0008, 0.0042)	0.0538***	(0.0523, 0.0552)	0.0268***	(0.0252, 0.0283)	0.0126***	(0.0105, 0.0147)	-0.0084***	(-0.0101, -0.0068)	0.0443***	(0.0412, 0.0474)
TAM	-0.1328***	(-0.1377, -0.1279)	0.0522***	(0.0491, 0.0552)	-0.0021*	(-0.0045, 0.0004)	0.0128***	(0.0105, 0.0151)	0.011***	(0.009, 0.0129)	-0.0246***	(-0.0259, -0.0233)
Thai Airways	0.0977***	(0.0921, 0.1032)	0.0183***	(0.0163, 0.0204)	0.0159***	(0.015, 0.0169)	-0.0235***	(-0.0254, -0.0216)	-0.0452***	(-0.0475, -0.043)	0.0285***	(0.0266, 0.0305)
Transavia.com (LCC)	-0.1536***	(-0.1599, -0.1473)	0.0656***	(0.0603, 0.071)	-0.0108***	(-0.0161, -0.0056)	-0.0086***	(-0.013, -0.0041)	-0.0184***	(-0.0217, -0.0152)	-0.0117***	(-0.0148, -0.0086)
United Airlines	0.0488***	(0.0432, 0.0545)	0.0402***	(0.0352, 0.0451)	0.0122***	(0.0075, 0.0169)	-0.0528***	(-0.058, -0.0477)	0.0151***	(0.0104, 0.0199)	0.0734***	(0.0667, 0.0802)
Virgin Australia (LCC)	-0.0231***	(-0.0274, -0.0188)	0.0752***	(0.0706, 0.0798)	0.0325***	(0.0277, 0.0374)	0.0203***	(0.0152, 0.0253)	-0.0156***	(-0.0195, -0.0116)	-0.0201***	(-0.0227, -0.0176)
WestJet (LCC)	-0.1041***	(-0.1094, -0.0987)	0.058***	(0.0541, 0.062)	0.0259***	(0.0222, 0.0296)	-0.0011	(-0.0041, 0.0019)	0.0018	(-0.0006, 0.0042)	0.0091***	(0.0071, 0.0111)

Note1: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Note2: Figures in parenthesis represent estimated 95% confidence intervals.

Appendix 7. System GMM estimation results (Dependent variables are estimated by joint model)

Dependent variable is $Productivity_{joint}$	Coefficient	Robust Std. Err.	z-value	P>|z|	[95% Conf. Interval]	
Constant	-0.027	0.732	-0.040	0.970	-1.462	1.408
$Productivity_{joint}$ one year lag	-0.075	0.146	-0.520	0.606	-0.362	0.211
$Productivity_{joint}$ two year lag	-0.119	0.099	-1.200	0.230	-0.313	0.075
Member	-0.122	0.246	-0.500	0.621	-0.603	0.360
LCC	0.077	0.063	1.220	0.221	-0.046	0.200
Ownership	-0.368	0.310	-1.190	0.236	-0.976	0.240
Demand	0.003	0.012	0.290	0.775	-0.019	0.026
Age	0.012	0.026	0.480	0.628	-0.038	0.063
Number of obs=136	Wald chi2(8)	15.48	Arellano-Bond test		Sargan test	
Number of groups=34	Prob > chi2	0.03	AR(1) Pr > z	0.027	chi2(6)	18.790
			AR(2) Pr > z	0.001	Prob > chi2	0.009

Dependent variable is $EFFCH_{joint}$	Coefficient	Robust Std. Err.	z-value	P>|z|	[95% Conf. Interval]	
Constant	0.233	0.355	0.660	0.512	-0.463	0.929
$EFFCH_{joint}$ one year lag	-0.299	0.127	-2.360	0.018	-0.547	-0.050
$EFFCH_{joint}$ two year lag	-0.232	0.104	-2.240	0.025	-0.435	-0.029
Member	-0.233	0.261	-0.890	0.372	-0.745	0.279
LCC	0.018	0.041	0.440	0.663	-0.062	0.098
Ownership	0.156	0.101	1.550	0.122	-0.042	0.354
Demand	-0.008	0.005	-1.570	0.115	-0.017	0.002
Age	0.037	0.041	0.910	0.361	-0.042	0.117
Number of obs=136	Wald chi2(8)	14.26	Arellano-Bond test		Sargan test	
Number of groups=34	Prob > chi2	0.05	AR(1) Pr > z	0.012	chi2(6)	19.790
			AR(2) Pr > z	0.551	Prob > chi2	0.006

Dependent variable is $TECHCH_{joint}$	Coefficient	Robust Std. Err.	z-value	P>|z|	[95% Conf. Interval]	
Constant	-0.251	0.452	-0.550	0.579	-1.137	0.635
$TECHCH_{joint}$ one year lag	0.310	0.224	1.380	0.167	-0.129	0.749
$TECHCH_{joint}$ two year lag	-0.024	0.113	-0.210	0.831	-0.247	0.198
Member	0.357	0.144	2.480	0.013	0.075	0.638
LCC	0.366	0.235	1.560	0.119	-0.094	0.826
Ownership	-0.242	0.194	-1.240	0.213	-0.623	0.139
Demand	0.003	0.008	0.420	0.672	-0.012	0.018
Age	-0.011	0.011	-1.030	0.302	-0.032	0.010
Number of obs=136	Wald chi2(8)	21.12	Arellano-Bond test		Sargan test	
Number of groups=34	Prob > chi2	0.004	AR(1) Pr > z	0.035	chi2(6)	10.940
			AR(2) Pr > z	0.617	Prob > chi2	0.141

Appendix 8. System GMM estimation results (Dependent variables are estimated by market model)

Dependent variable is $Productivity_{market}$	Coefficient	Robust Std. Err.	z-value	P>|z|	[95% Conf. Interval]	
Constant	-3.842	2.791	-1.380	0.169	-9.312	1.629
$Productivity_{market}$ one year lag	-0.299	0.277	-1.080	0.281	-0.842	0.245
$Productivity_{market}$ two year lag	-0.377	0.274	-1.380	0.169	-0.914	0.160
Member	-2.803	1.793	-1.560	0.118	-6.317	0.711
LCC	1.228	0.774	1.590	0.112	-0.288	2.745
Ownership	-1.280	0.994	-1.290	0.198	-3.228	0.669
Demand	0.003	0.022	0.130	0.898	-0.041	0.047
Age	0.614	0.393	1.560	0.118	-0.156	1.384
Number of obs=136	Wald chi2(8)	3.79	Arellano-Bond test		Sargan test	
Number of groups=34	Prob > chi2	0.804	AR(1) Pr > z	0.923	chi2(6)	0.810
			AR(2) Pr > z	0.702	Prob > chi2	0.997

Dependent variable is $EFFCH_{market}$	Coefficient	Robust Std. Err.	z-value	P>|z|	[95% Conf. Interval]	
Constant	0.667	0.543	1.230	0.220	-0.398	1.731
$EFFCH_{market}$ one year lag	-0.220	0.095	-2.320	0.020	-0.407	-0.034
$EFFCH_{market}$ two year lag	-0.132	0.060	-2.220	0.026	-0.249	-0.015
Member	0.017	0.221	0.080	0.937	-0.415	0.450
LCC	0.211	0.132	1.600	0.110	-0.048	0.470
Ownership	0.277	0.157	1.760	0.078	-0.031	0.584
Demand	-0.017	0.007	-2.520	0.012	-0.031	-0.004
Age	0.043	0.049	0.880	0.380	-0.053	0.140
Number of obs=136	Wald chi2(8)	30.85	Arellano-Bond test		Sargan test	
Number of groups=34	Prob > chi2	0.000	AR(1) Pr > z	0.042	chi2(6)	31.730
			AR(2) Pr > z	0.000	Prob > chi2	0.000

Dependent variable is $TECHCH_{market}$	Coefficient	Robust Std. Err.	z-value	P>|z|	[95% Conf. Interval]	
Constant	-0.682	0.320	-2.130	0.033	-1.310	-0.055
$TECHCH_{market}$ one year lag	-0.168	0.134	-1.260	0.209	-0.431	0.094
$TECHCH_{market}$ two year lag	-0.056	0.077	-0.720	0.471	-0.207	0.096
Member	-0.011	0.093	-0.120	0.906	-0.194	0.172
LCC	-0.094	0.105	-0.900	0.368	-0.300	0.111
Ownership	0.177	0.214	0.830	0.409	-0.243	0.596
Demand	0.009	0.004	2.140	0.032	0.001	0.017
Age	-0.009	0.016	-0.580	0.565	-0.040	0.022
Number of obs=136	Wald chi2(8)	12.48	Arellano-Bond test		Sargan test	
Number of groups=34	Prob > chi2	0.086	AR(1) Pr > z	0.000	chi2(6)	12.730
			AR(2) Pr > z	0.393	Prob > chi2	0.079